

## Stochastic facility location problems with outsourcing costs

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# Problem definition: a two-stage stochastic problem

- · First stage: an "assignment" problem.
  - Facility location: Customers assigned to open facilities
  - · Generalized Assignment: Tasks assigned to agents
  - Vehicle Routing: Customers assigned to vehicles
- · Second stage: an stochastic demand to be served with outsourcing/penalty.
  - Customer/task demands are served by the assigned facility/agent/vehicle minimizing cost.
  - If the total demand is higher than the capacity, the unserved demands is outsourced / penalized at a higher cost.
- Objective: Minimize the assignment cost + expected value of serving demand.
- This talk: Solve the problem for general probability distributions (not scenarios)



$$\min \sum_{i} f_{i}y_{i} + \sum_{i} \sum_{j} g_{ij}d_{j}x_{ij}$$

$$x_{ij} \leq y_{i}$$

$$(x, y) \in \mathcal{X}$$

$$x, y \in \{0, 1\}$$

Given a set of customers J with demand  $d_j$  and a set of potential facilities I  $d_j$ =3 to decide a subset of facilities to open  $(y_i = 1)$  and an assignment of customers to facilities  $(x_{ij} = 1)$  to fulfill the demand of clients minimizing the installment fix costs  $f_i$  and assignment costs  $g_{ij}$ 

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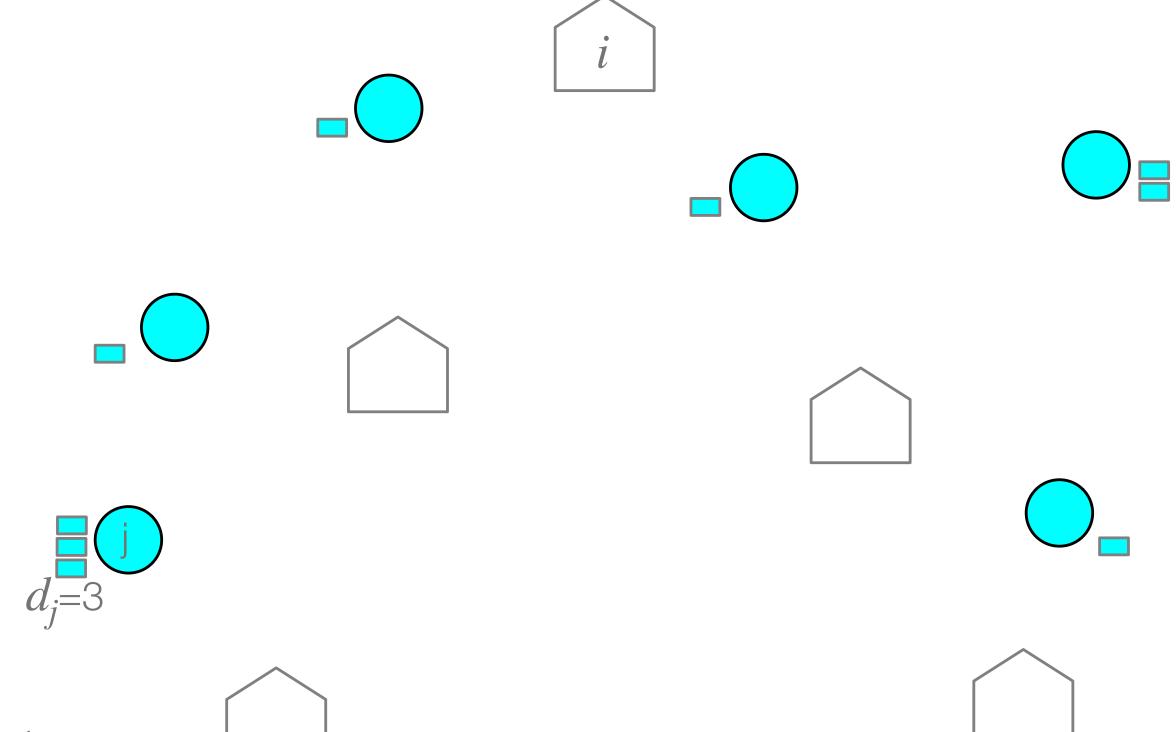
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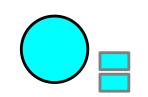
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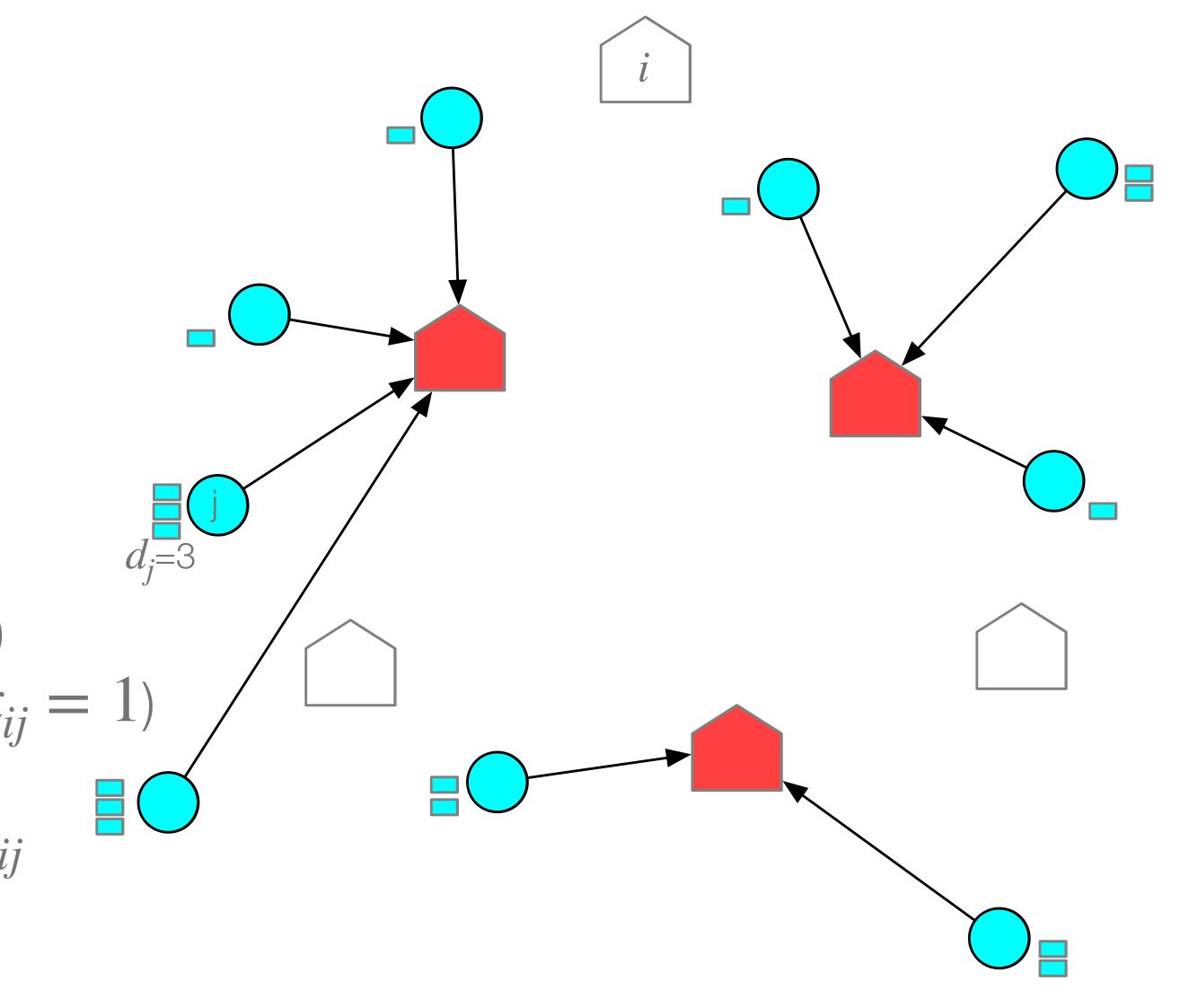
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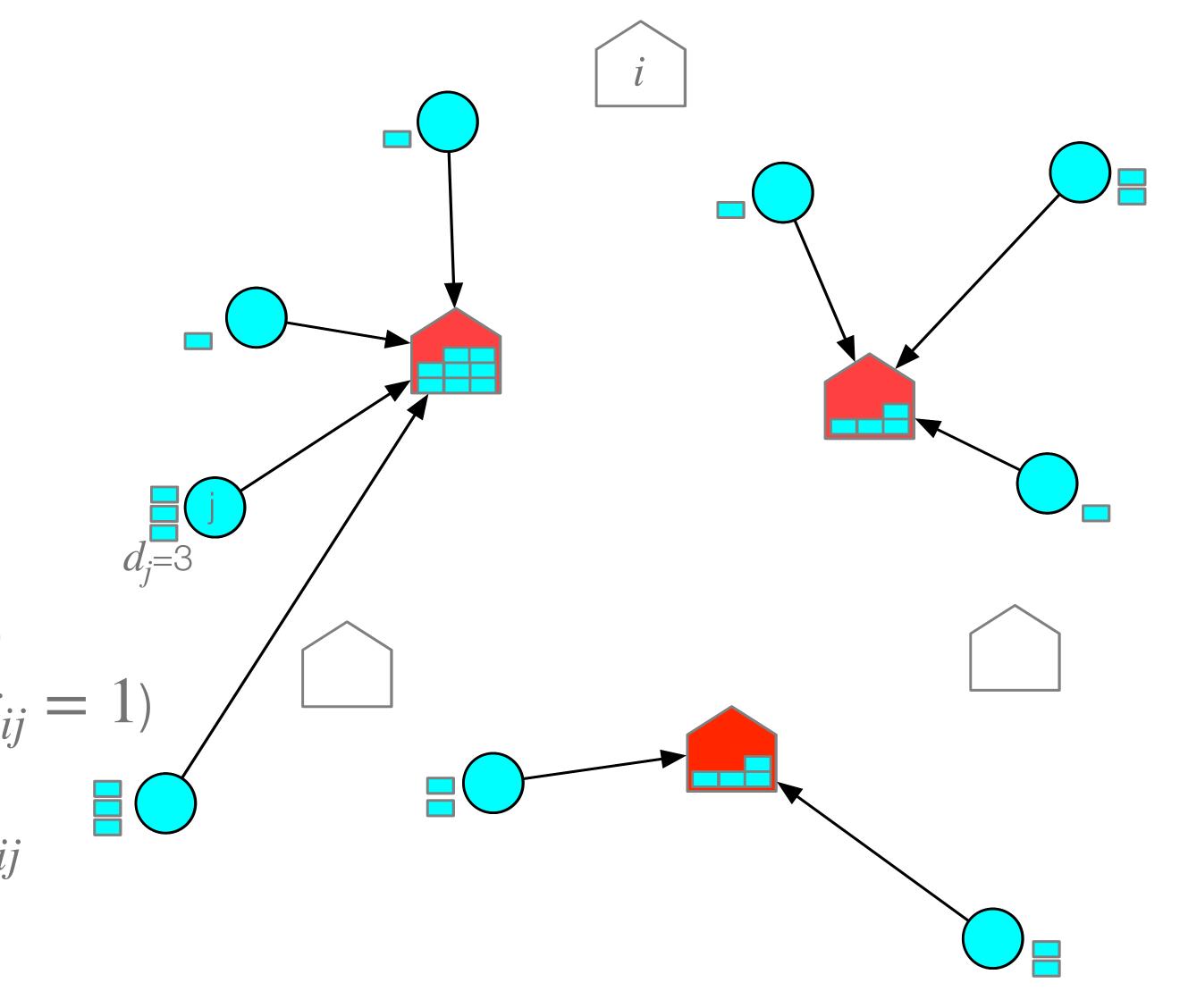
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## Capacitated Facility Location

$$\min \sum_{i} f_{i}y_{i} + \sum_{i} \sum_{j} g_{ij}d_{j}x_{ij}$$

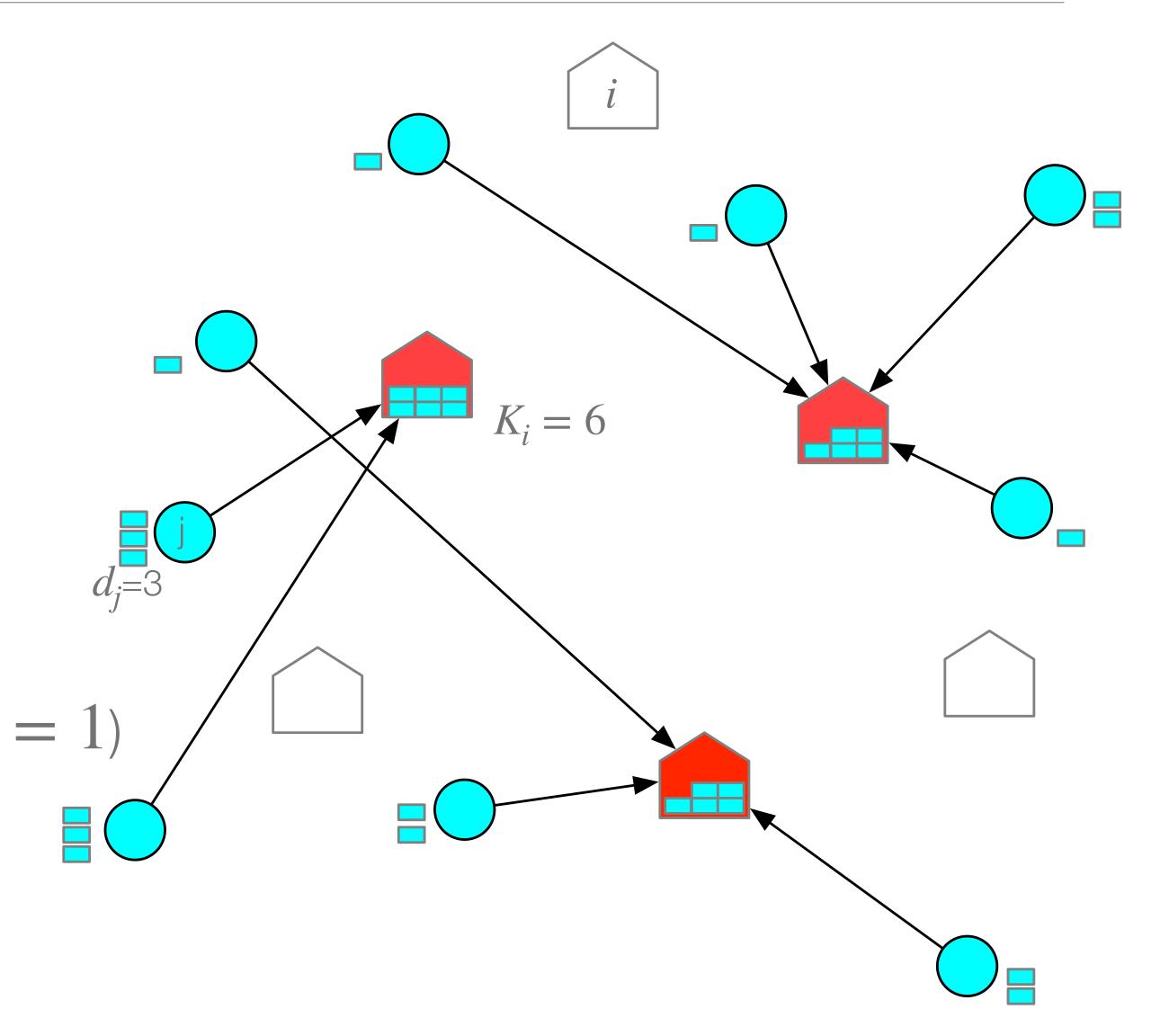
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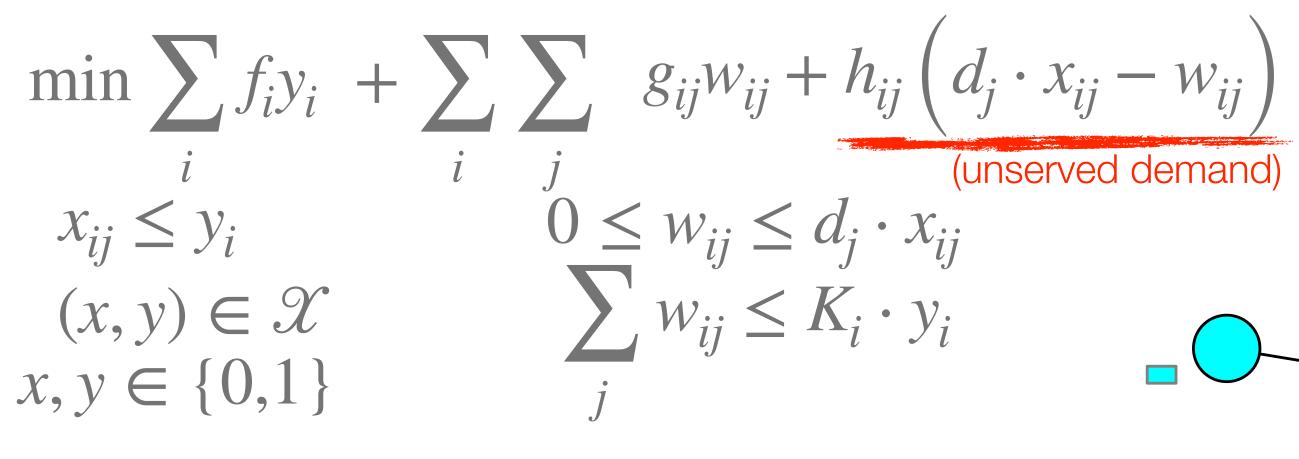
$$\sum_{j} d_{j}x_{ij} \leq K_{i} \cdot y_{i}$$

Given a set of customers J with demand  $d_j$  and a set of potential facilities I to decide a subset of facilities to open  $(y_i = 1)$  and an assignment of customers to facilities  $(x_{ij} = 1)$  to fulfill the demand of clients minimizing the installment fix costs  $f_i$  and assignment costs  $g_{ij}$  while satisfying the capacity of the facility  $K_i$ 





# Capacitated Facility Location with Outsourcing



Given a set of customers J with demand  $d_j$  and a set of potential facilities I

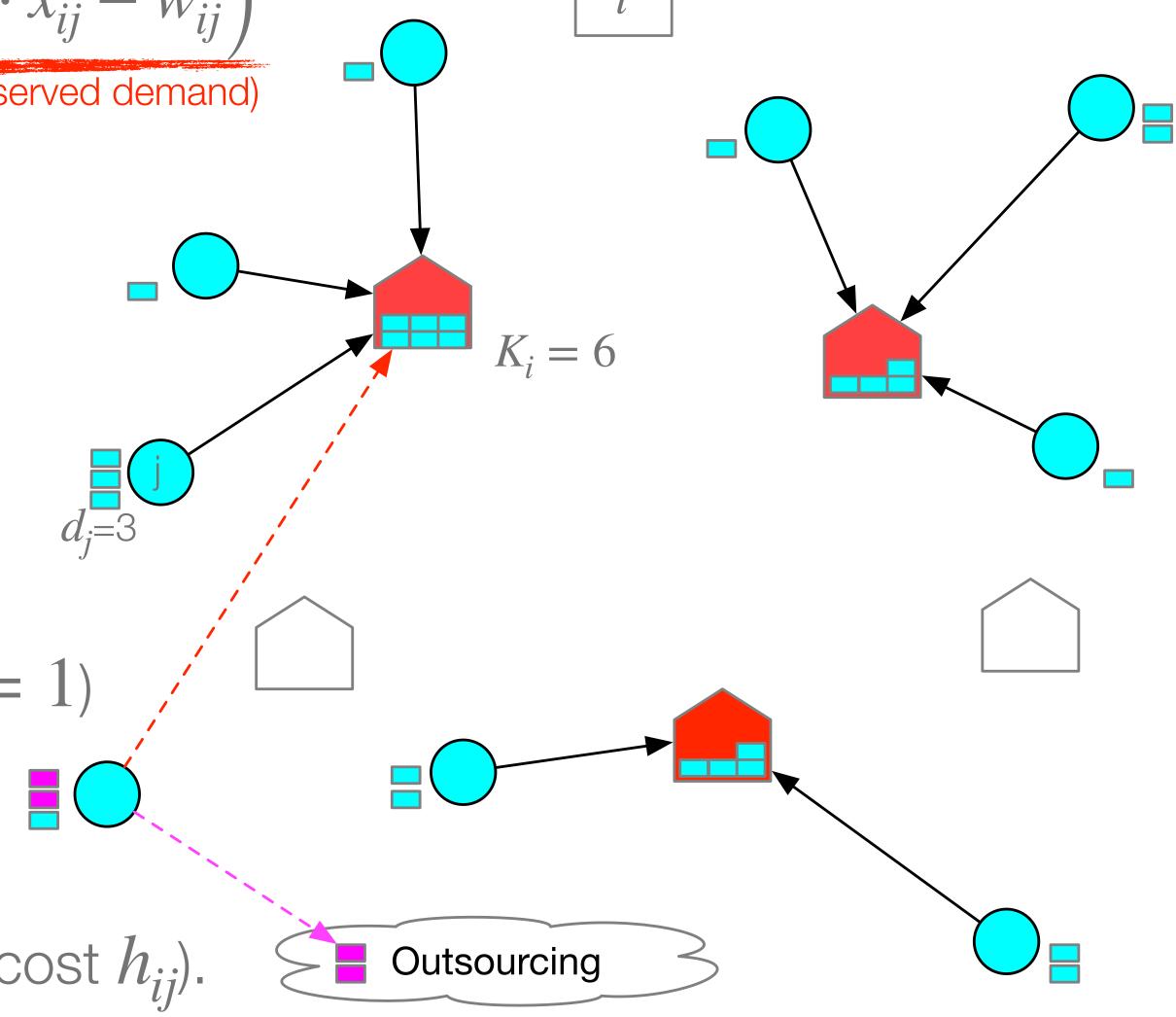
to decide a subset of facilities to open  $(y_i = 1)$ 

and an assignment of customers to facilities ( $x_{ij} = 1$ )

to fulfill the demand of clients minimizing the installment fix costs  $f_i$  and assignment costs  $g_{ii}$ 

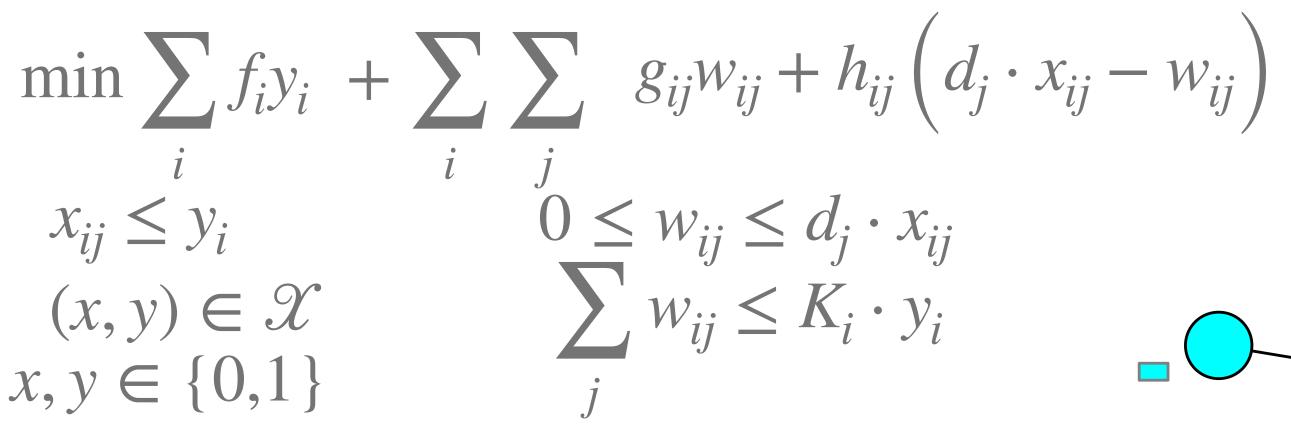
while satisfying the capacity of the facility  $\boldsymbol{K}_i$ 

allowing to outsource some demand (at a higher cost  $h_{ii}$ ).





# Capacitated Facility Location with Outsourcing



Given a set of customers J with demand  $d_j$  and a set of potential facilities I

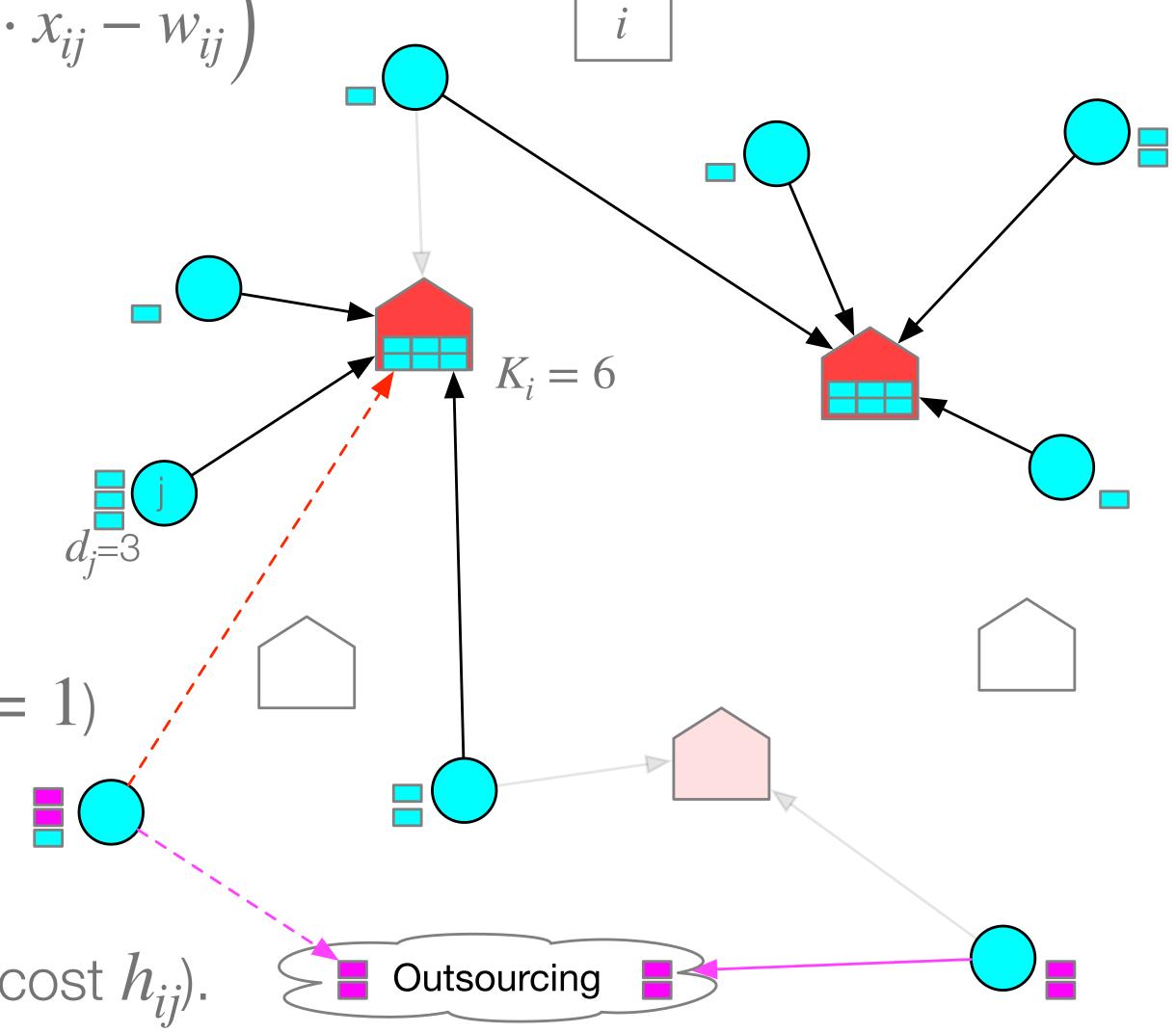
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and an assignment of customers to facilities ( $x_{ii} = 1$ )

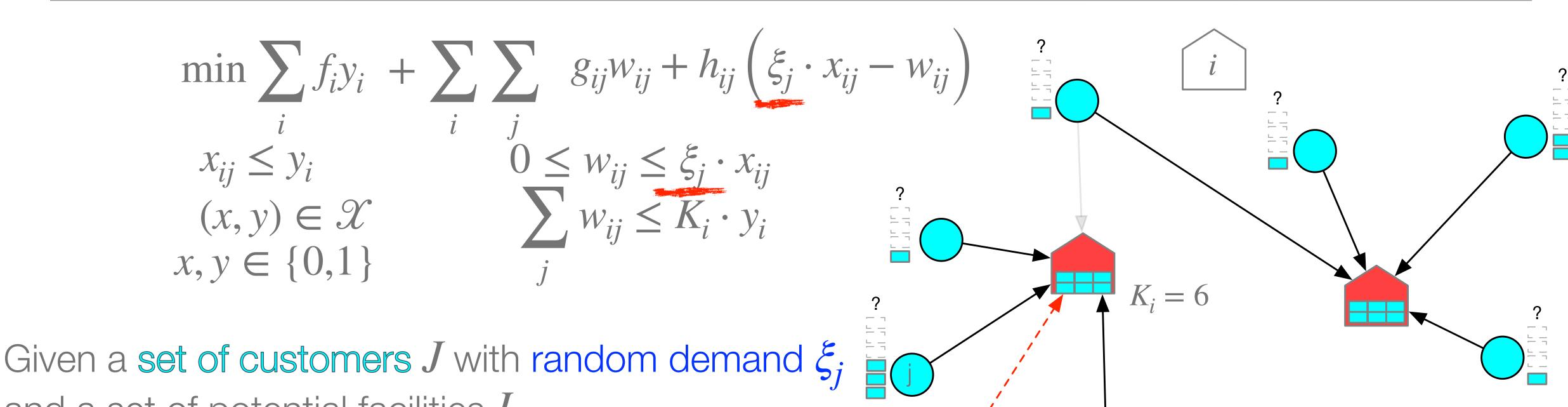
to fulfill the demand of clients minimizing the installment fix costs  $f_i$  and assignment costs  $g_{ii}$ 

while satisfying the capacity of the facility  $K_i$ 

allowing to outsource some demand (at a higher cost  $h_{ii}$ ).







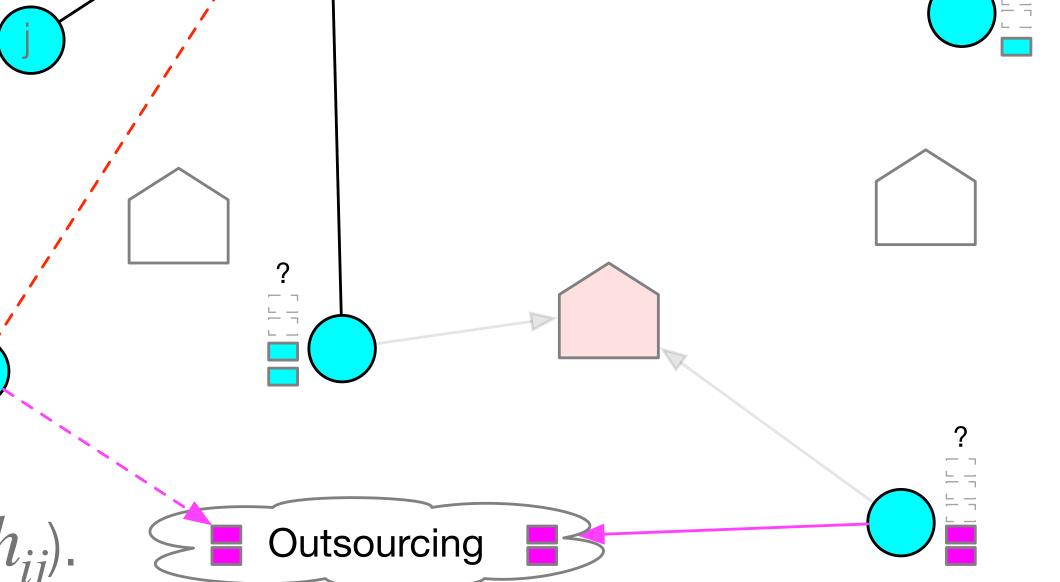
and a set of customers J with random demand  $\zeta$  and a set of potential facilities I to decide a subset of facilities to open  $(y_i = 1)$ 

and an assignment of customers to facilities  $(x_{ij} = 1)$ 

to fulfill the demand of clients minimizing the installment fix costs  $f_i$  and assignment costs  $g_{ii}$ 

while satisfying the capacity of the facility  $K_i$ 

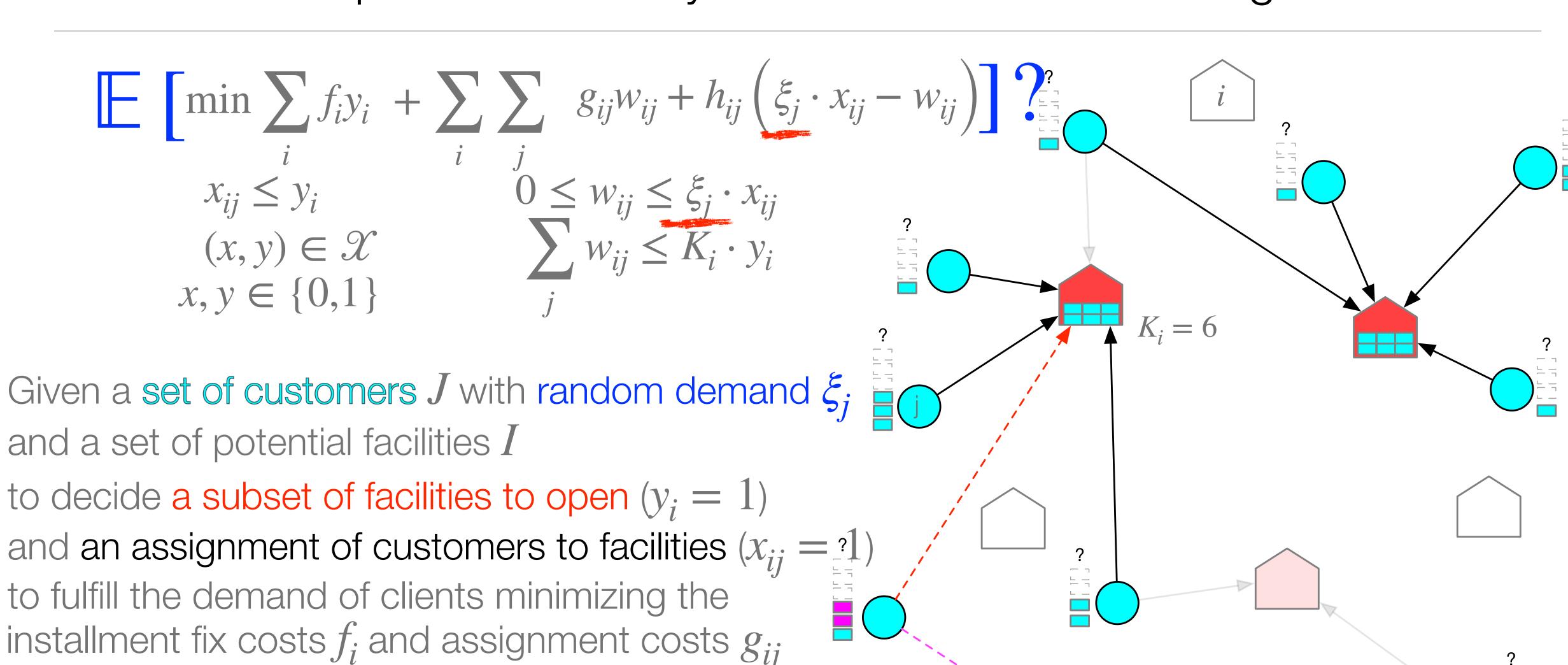
allowing to outsource some demand (at a higher cost  $h_{ij}$ ).





Outsourcing =

## Stochastic Capacitated Facility Location with Outsourcing



while satisfying the capacity of the facility  $K_i$  allowing to outsource some demand (at a higher cost  $h_{ij}$ ).



$$\min \sum_{i} f_{i}y_{i} + \sum_{i} \sum_{j} \mathbb{E} \left[ g_{ij}w_{ij} + h_{ij} \left( \xi_{j} \cdot x_{ij} - w_{ij} \right) \right]$$

$$x_{ij} \leq y_{i}$$

$$(x, y) \in \mathcal{X}$$

$$x, y \in \{0, 1\}$$

$$j$$

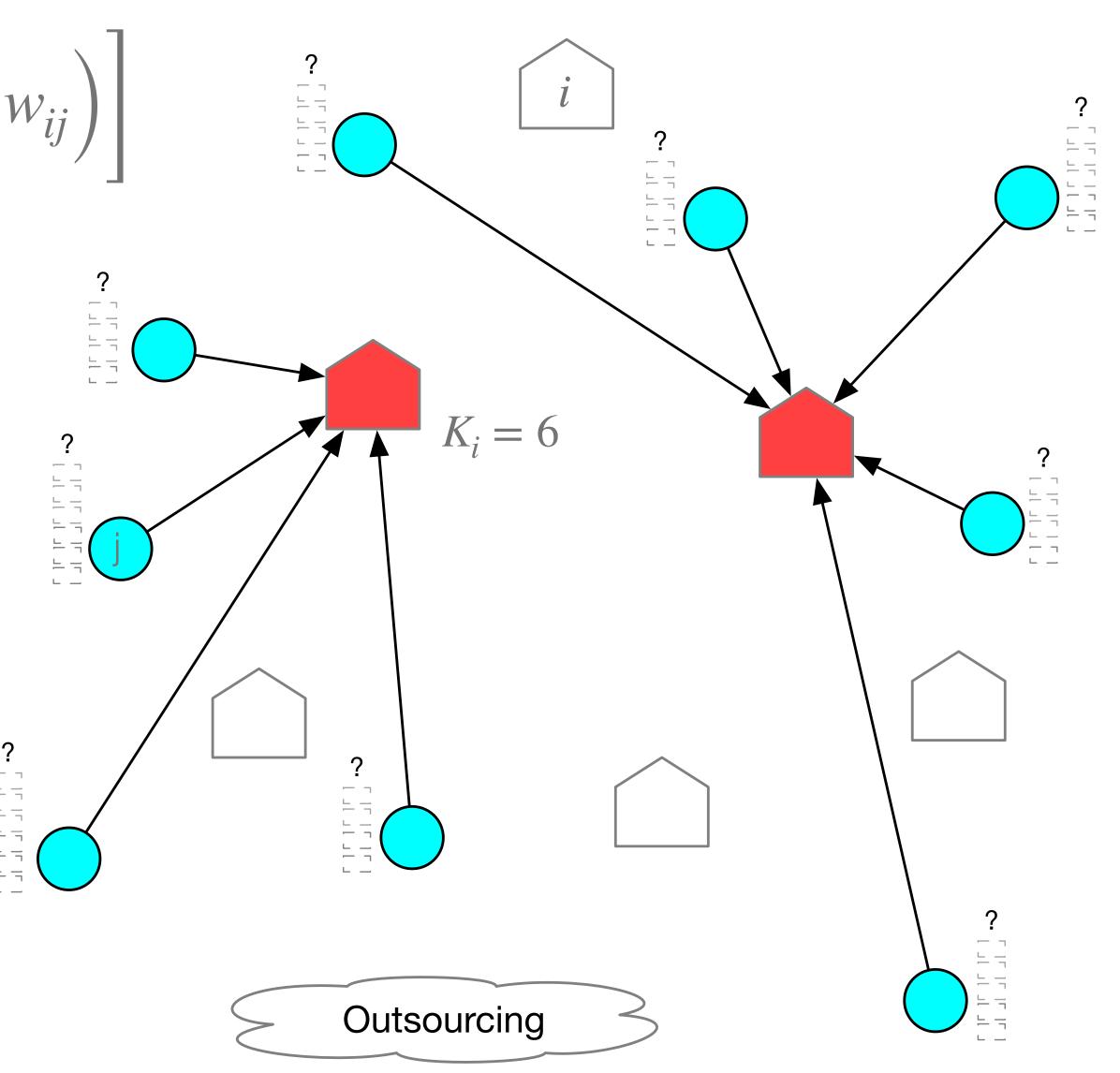
$$0 \leq w_{ij} \leq \xi_{j} \cdot x_{ij}$$

$$\sum_{j} w_{ij} \leq K_{i} \cdot y_{i}$$

$$j$$

We assume a two-stage stochastic problem:

• 1st stage decision (here-and-now): to open facilities and assign customers to them.





$$\min \sum_{i} f_{i}y_{i} + \sum_{i} \sum_{j} \mathbb{E} \left[ g_{ij}w_{ij} + h_{ij} \left( \xi_{j} \cdot x_{ij} - w_{ij} \right) \right]$$

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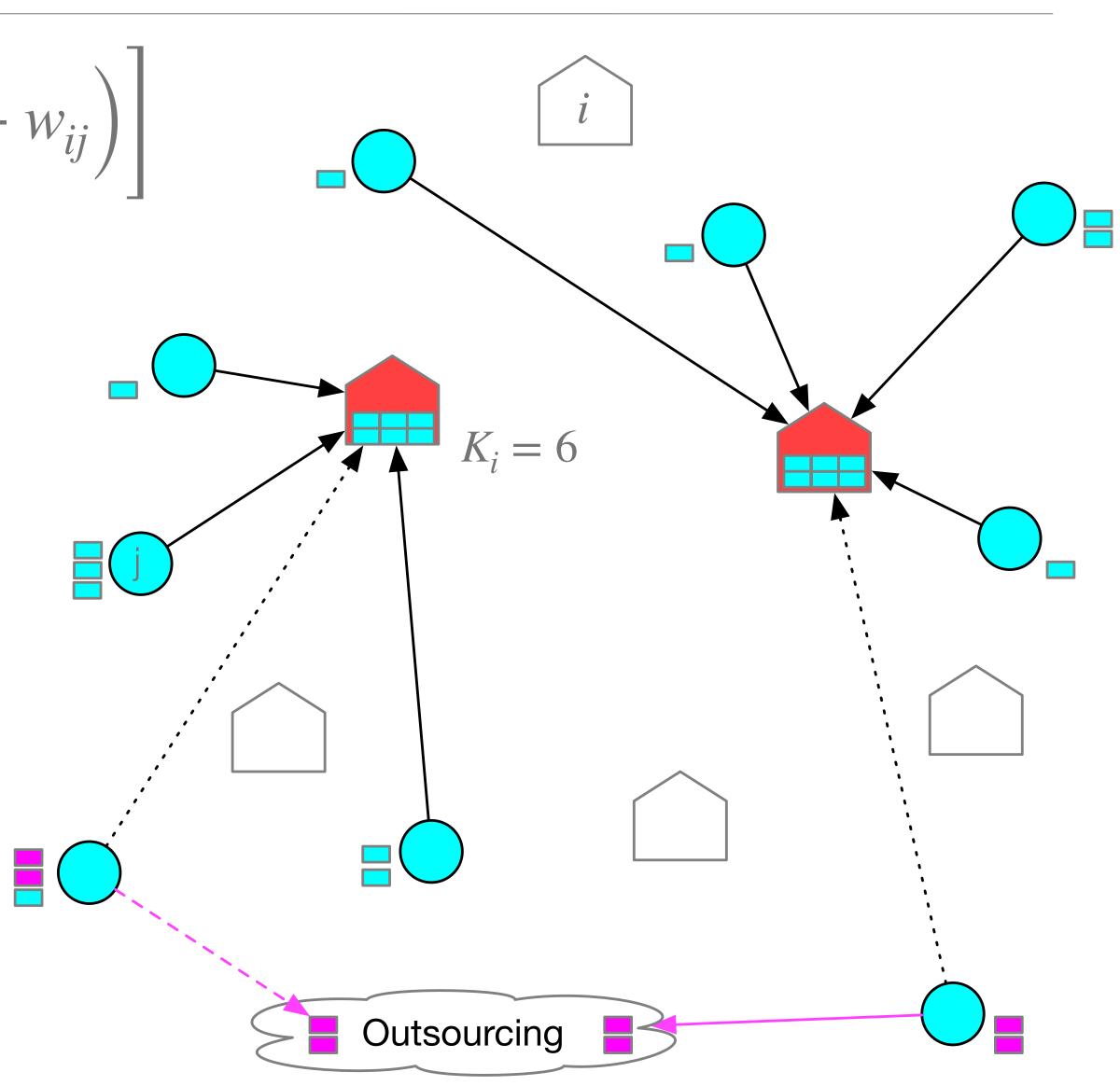
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- 1st stage decision (here-and-now): to open facilities and assign customers to them.
- 2nd stage decision (wait-and-see): to route and/or outsource the random demand.





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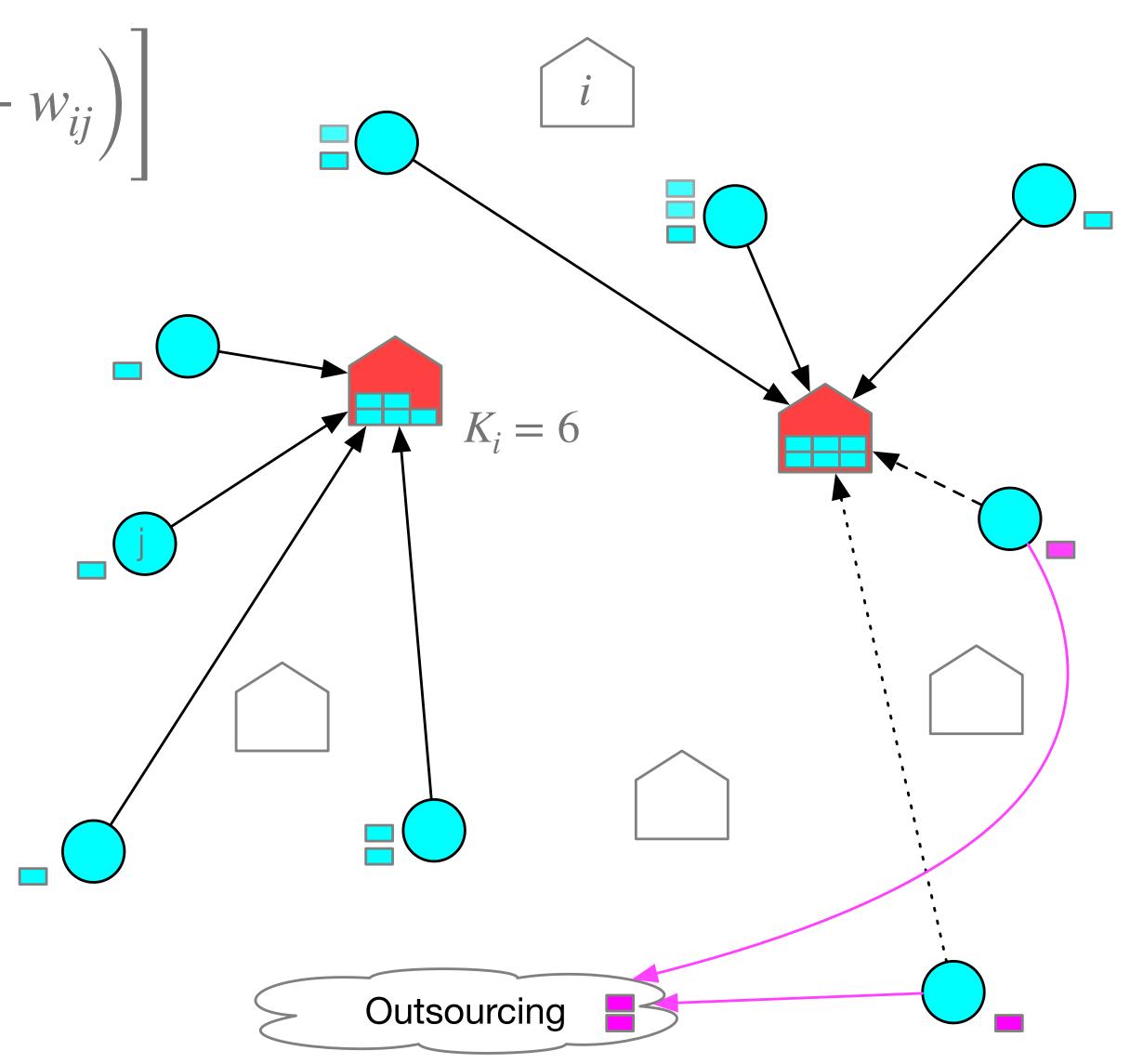
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$$\min \sum_{i} f_{i}y_{i} + \sum_{i} \sum_{j} \mu_{j}h_{ij}x_{ij} - \sum_{i} \mathbb{E} \left[ \sum_{j} (h_{ij} - g_{ij})w_{ij} \right]$$

$$x_{ij} \leq y_{i}$$

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$$\min \sum_{i} f_{i}y_{i} + \sum_{i} \sum_{j} \mu_{j}h_{ij}x_{ij} - \sum_{i} \mathbb{E}[Q^{i}(x, y, \xi)]$$

$$x_{ij} \leq y_{i}$$

$$(x, y) \in \mathcal{X}$$

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First-stage problem

We assume a two-stage stochastic problem:

- 1st stage decision (here-and-now): to open facilities and assign customers to them.
- 2nd stage decision (wait-and-see): to route and/or outsource the random demand.

$$Q^{i}(x, y, \xi) = \max_{w \ge 0} \sum_{j} c_{ij} w_{ij}$$
$$w_{ij} \le \xi_{j} \cdot x_{ij}$$
$$\sum_{i} w_{ij} \le K_{i} \cdot y_{i}$$

Second-stage problem (independent for each facility)



# Application example.

Partnership between Google and Ignite Energy Access to deploy solar panels in Africa, with focus on remote rural areas.



#### **Bloomberg**



A mini-grid provides power to the community in Nyimba Mwana village in the Eastern Province of Zambia, on Feb. 20.

#### THE MISSION TO ELECTRIFY AFRICA MIGHT FINALLY BE UNDER WAY

Plunging solar panel prices and international funding are now spurring the rollout of so-called mini grids that can transform rural communities

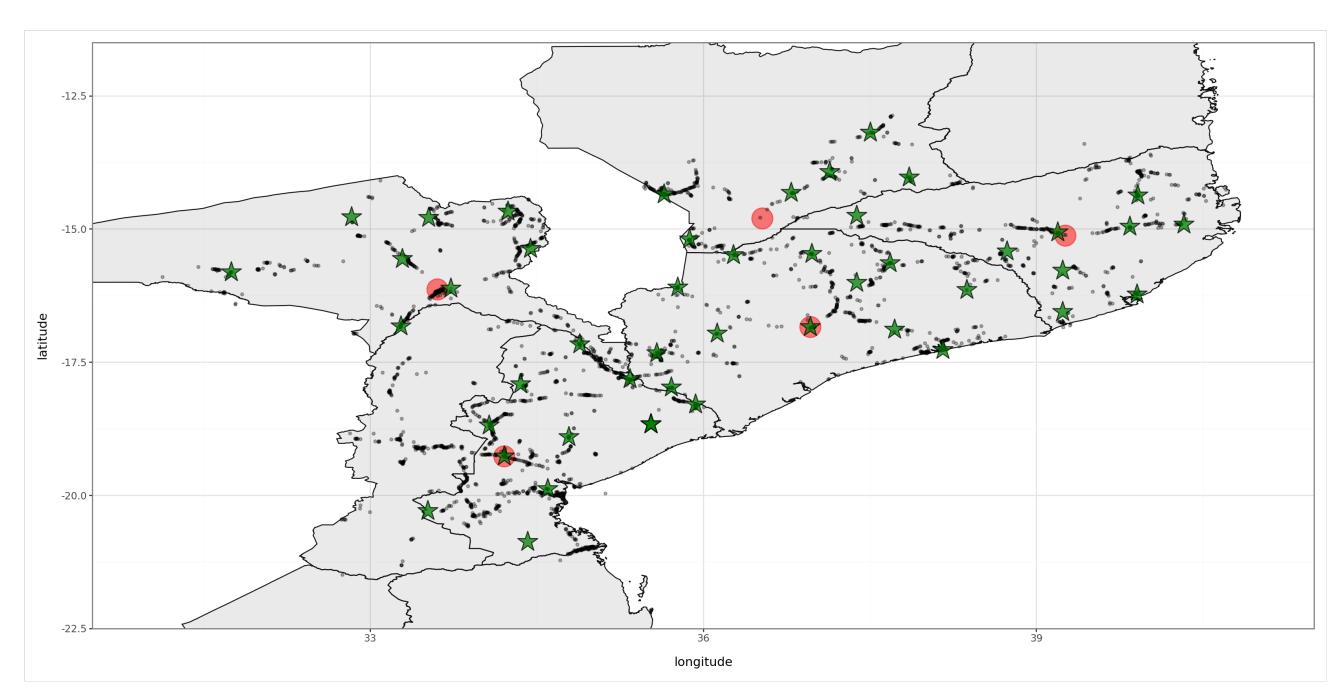


(Images from <a href="https://igniteaccess.com/media/">https://igniteaccess.com/media/</a>)



# Application example.

- Facilities: "minihubs" with containers of solar panels. Very expensive due to the lack of roads.
- Customers: small villages in the country side of Mozambique.
- Agents visit customers by foot or bikes due the lack of roads.
- Uncertainty: adoption of the technology in the villages.





# Stochastic facility location problems with outsourcing costs

- 1. Bender formulation for a <u>discrete set of scenarios</u> (for example, a sample average approximation of the demand distributions)
- 2. Bender formulation for general distributions.
- 3. Strengthened formulation.
- 4. Computational experiments

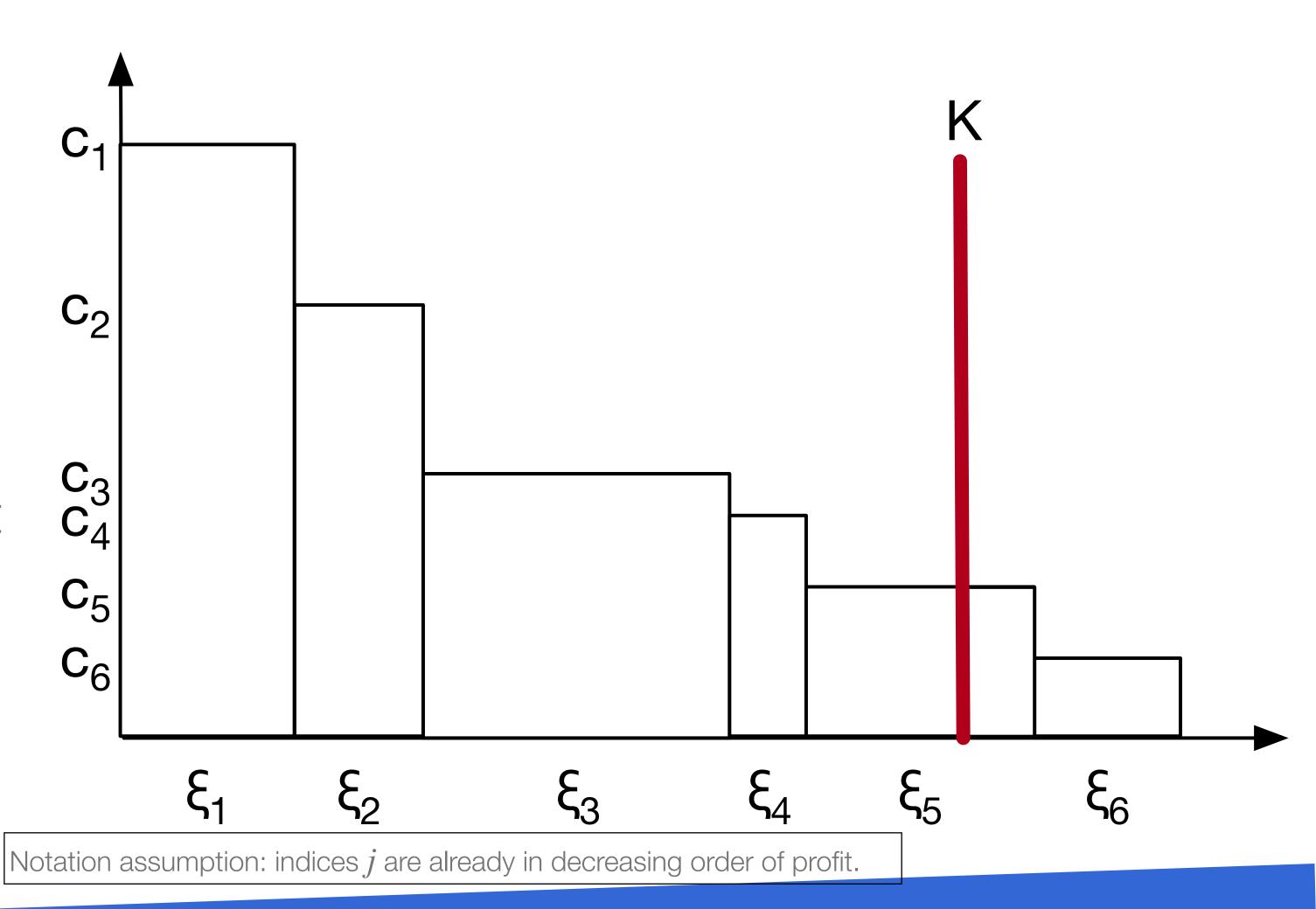


$$Q^{i}(x, y, \xi) = \max_{w \ge 0} \sum_{j} c_{ij} w_{ij}$$

$$w_{ij} \le \xi_{j} \cdot x_{ij}$$

$$\sum_{j} w_{ij} \le K_{i} \cdot y_{i}$$

$$w_{ij} = \begin{cases} \xi_j x_{ij} & j < \tau^i \\ K_i y_i - \sum_{l < \tau^i} x_{il} \xi_l & j = \tau^i \\ 0 & j > \tau^i \end{cases}$$



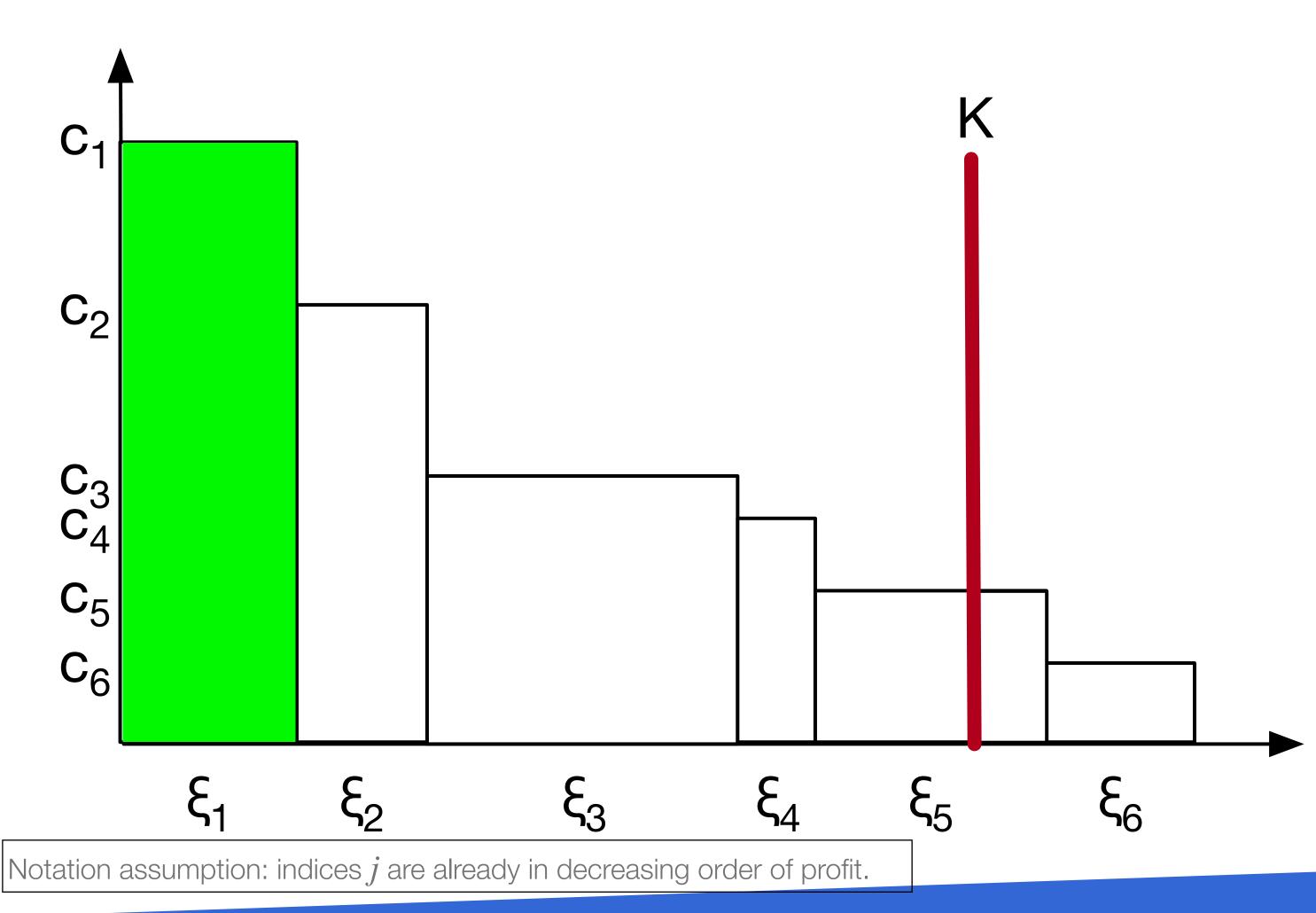


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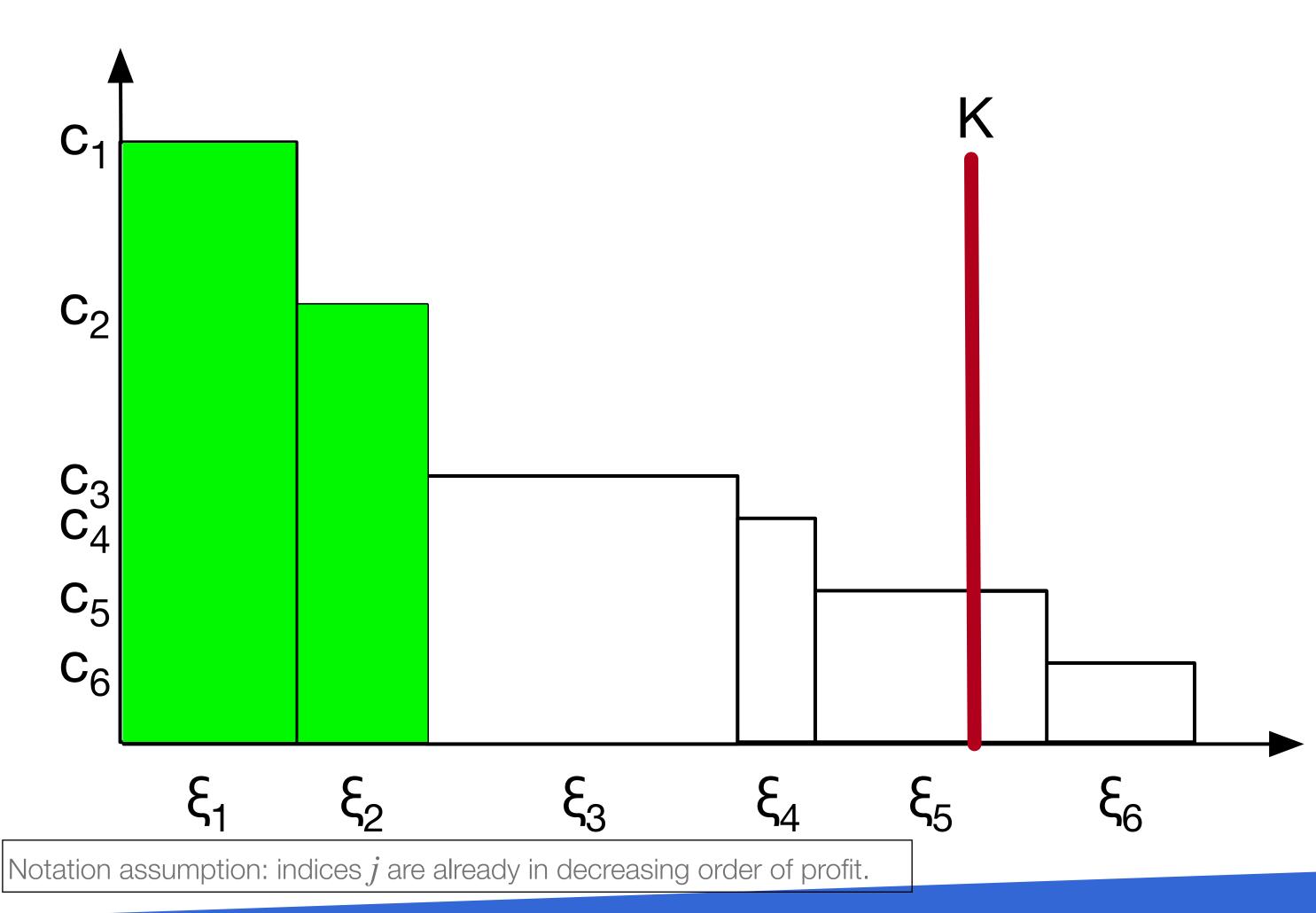


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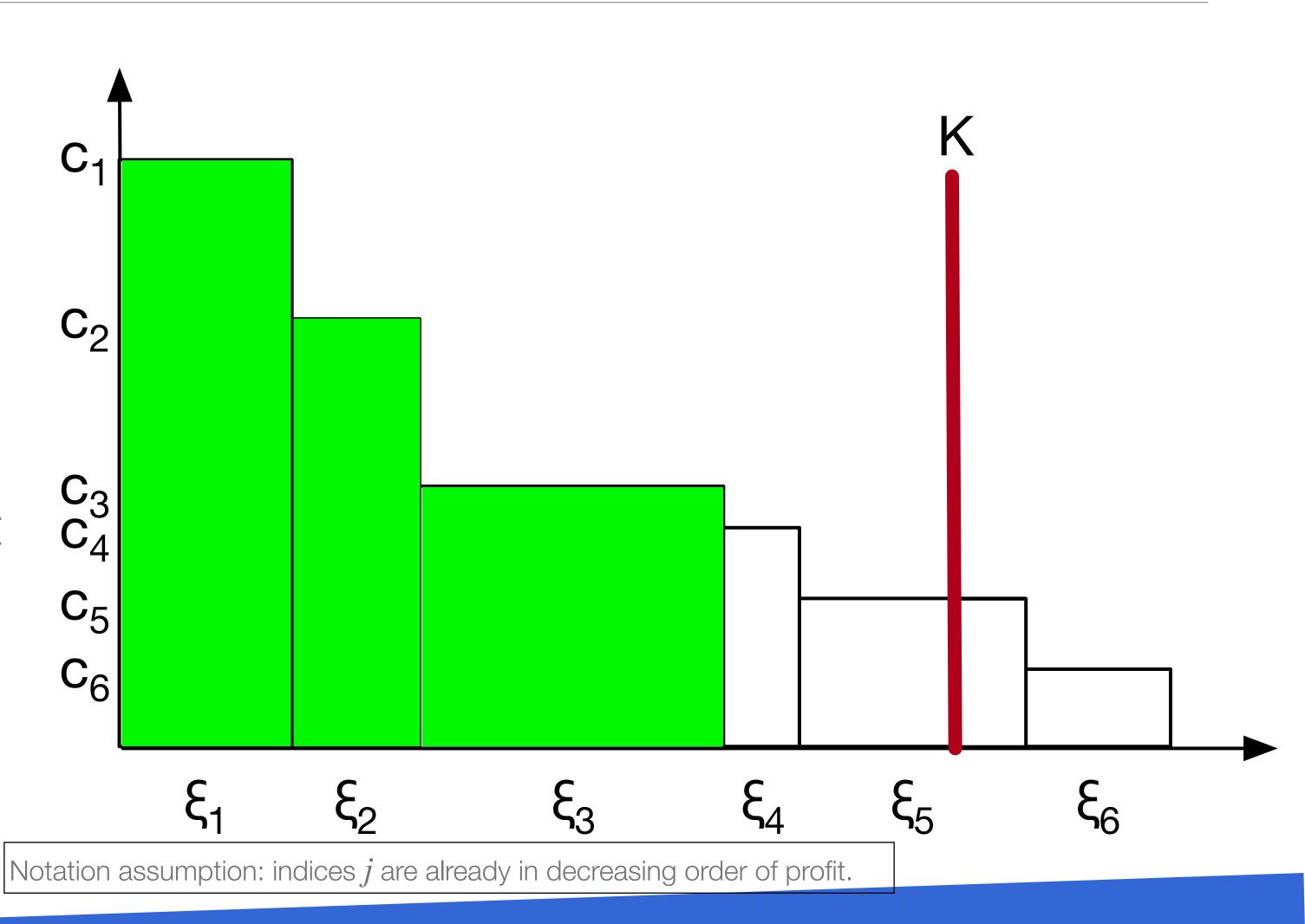


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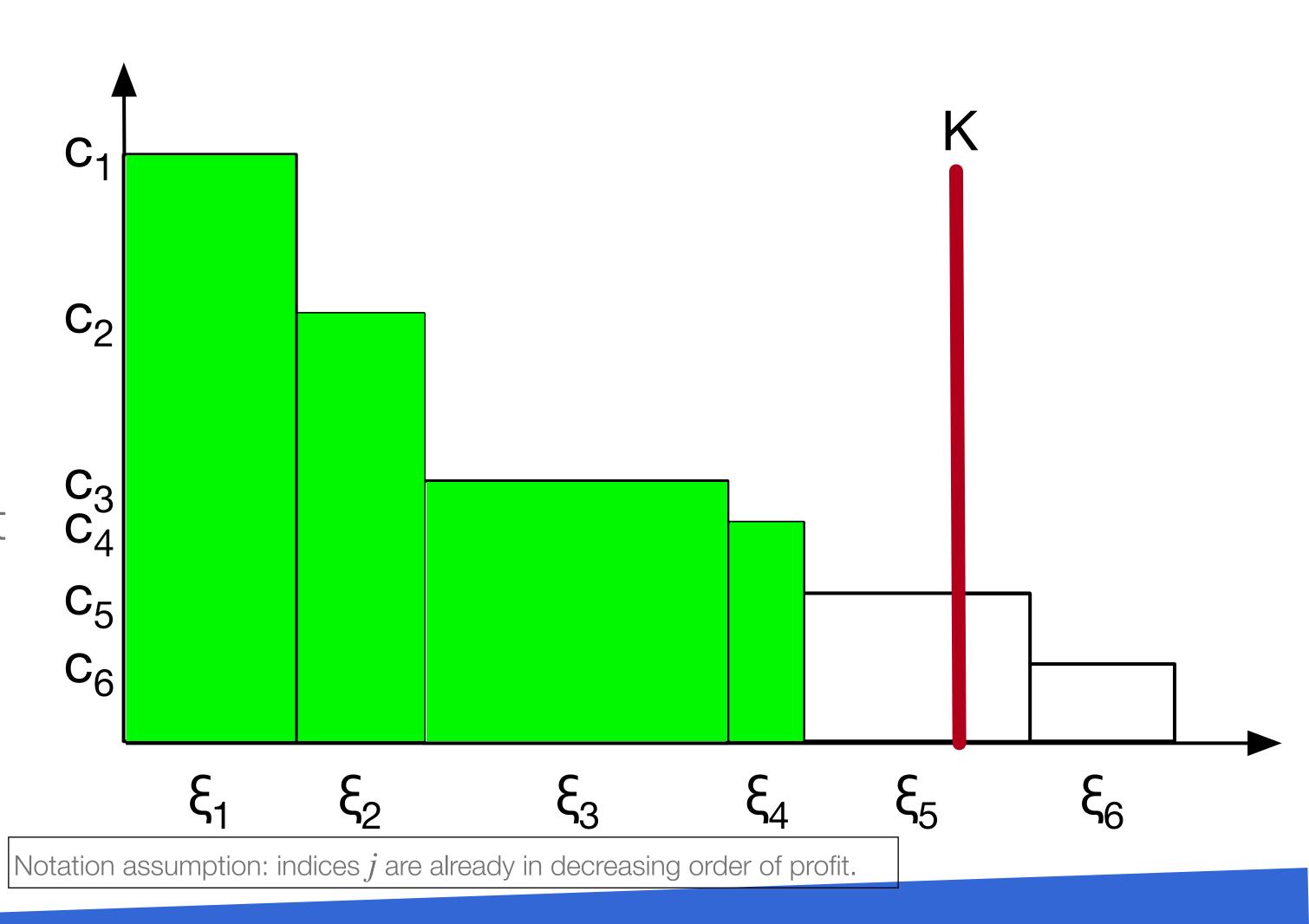


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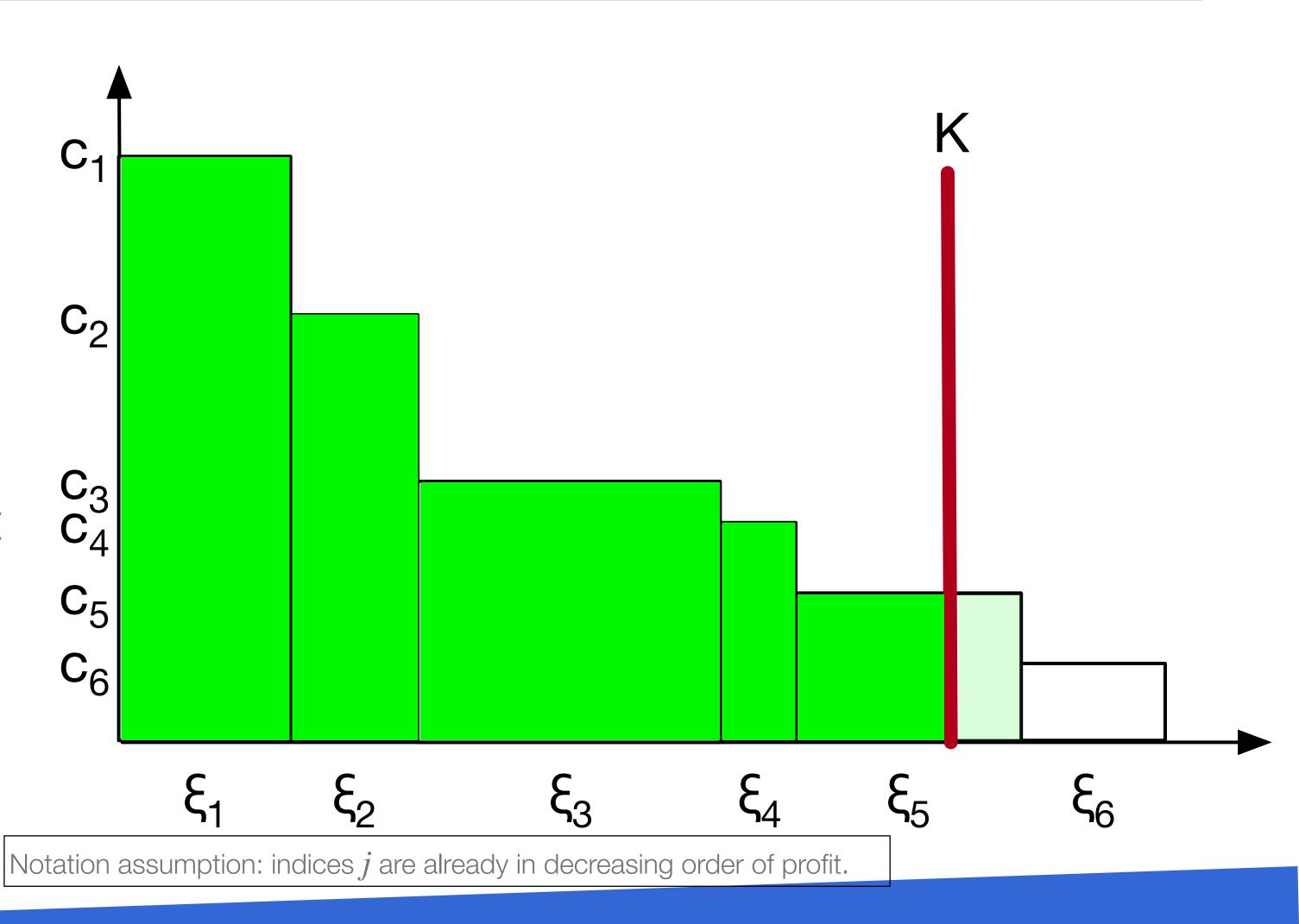


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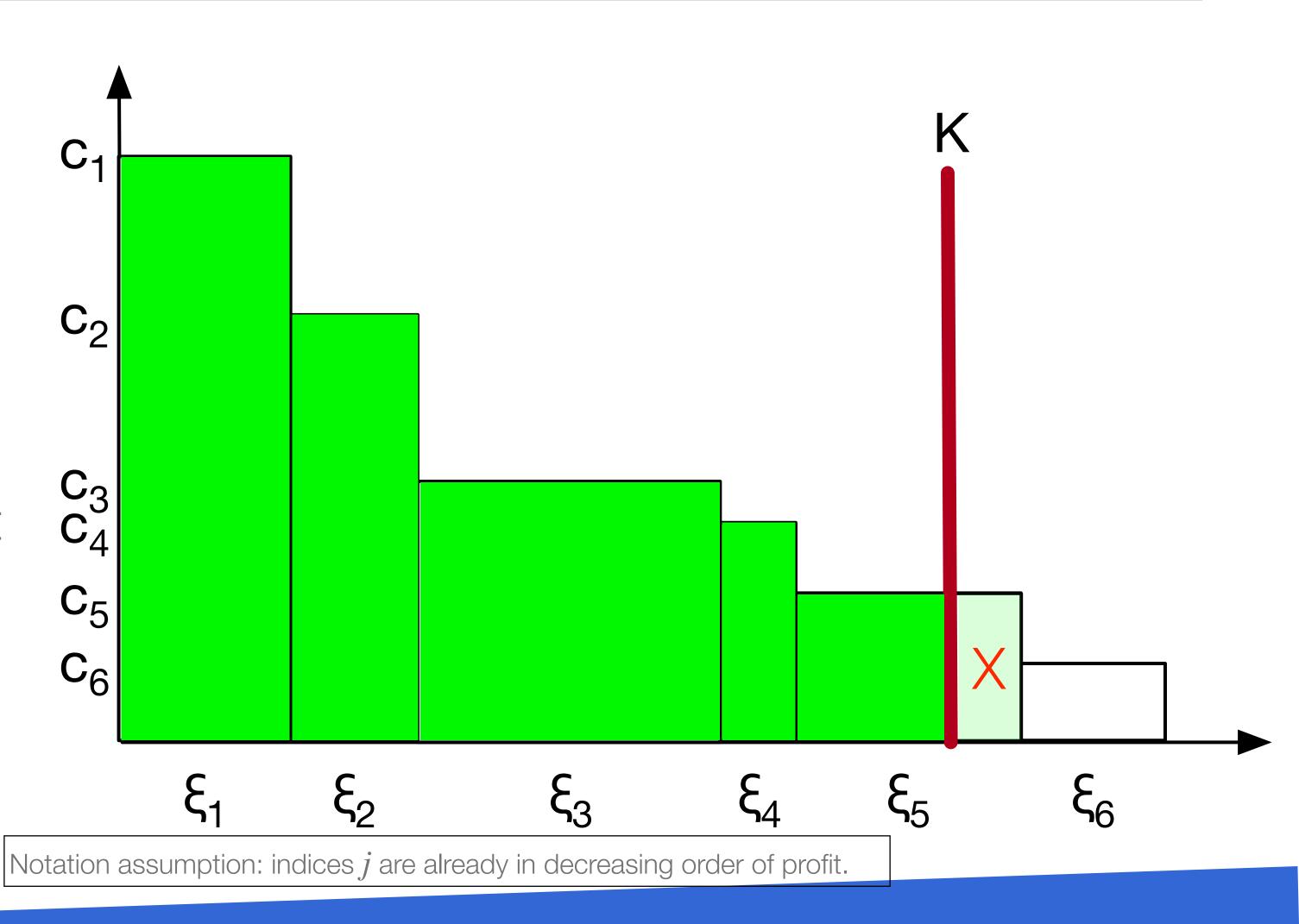


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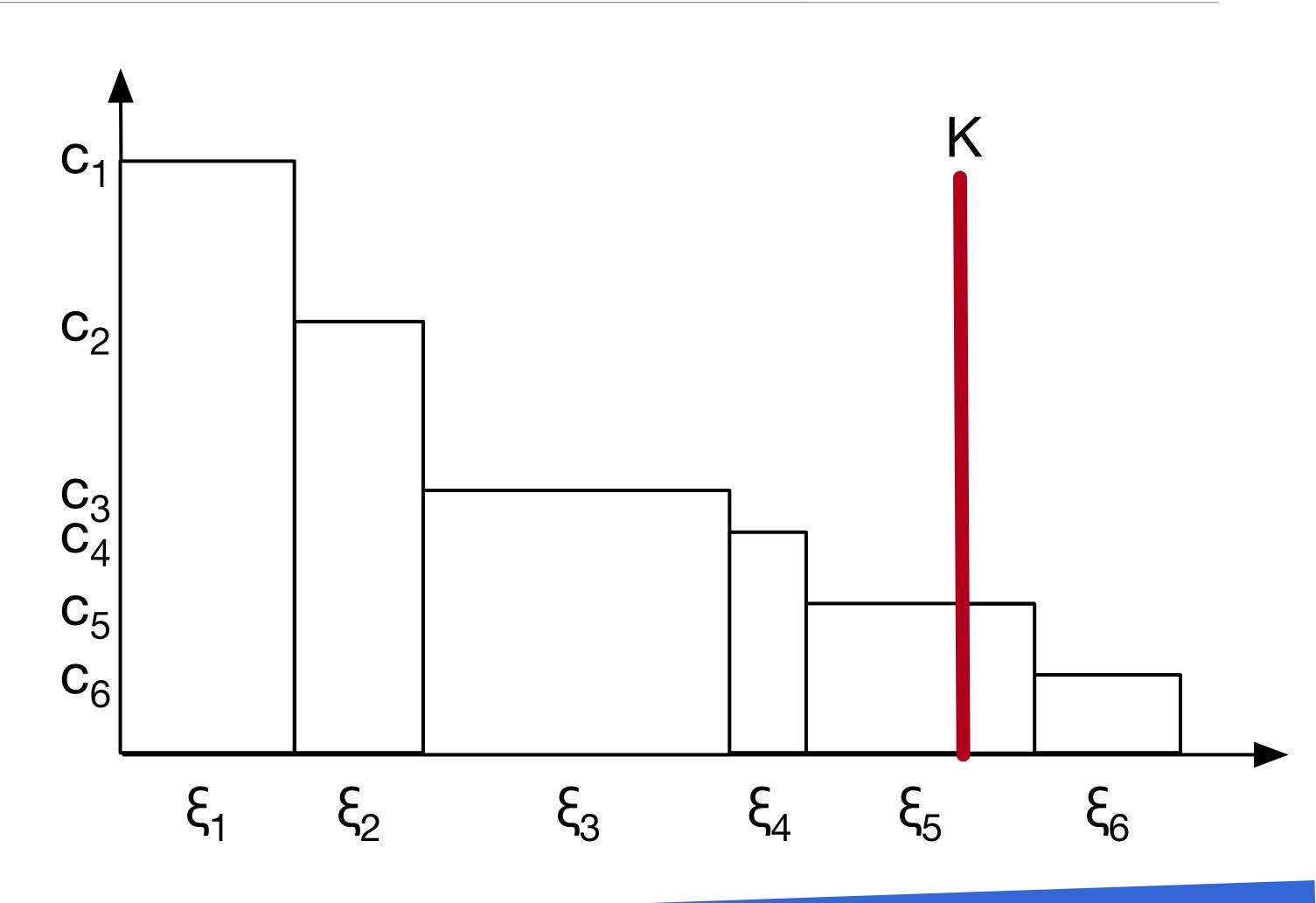
Dual of the subproblem is given by

$$\min_{\alpha \ge 0, \gamma \ge 0} \sum_{j \in J} \alpha_{ij} \xi_j x_{ij} + \gamma_i K_i y_i$$

$$\alpha_{ij} + \gamma_i \ge c_{ij} \qquad \forall j \in J$$

and its optimal solution is given by

$$\gamma_i = \begin{cases} \hat{c}_i^{\xi} & y_i^* > 0 \\ 0 & y_i^* = 0 \end{cases} \quad \alpha_{ij} = (c_{ij} - \hat{c}_i^{\xi})^+$$





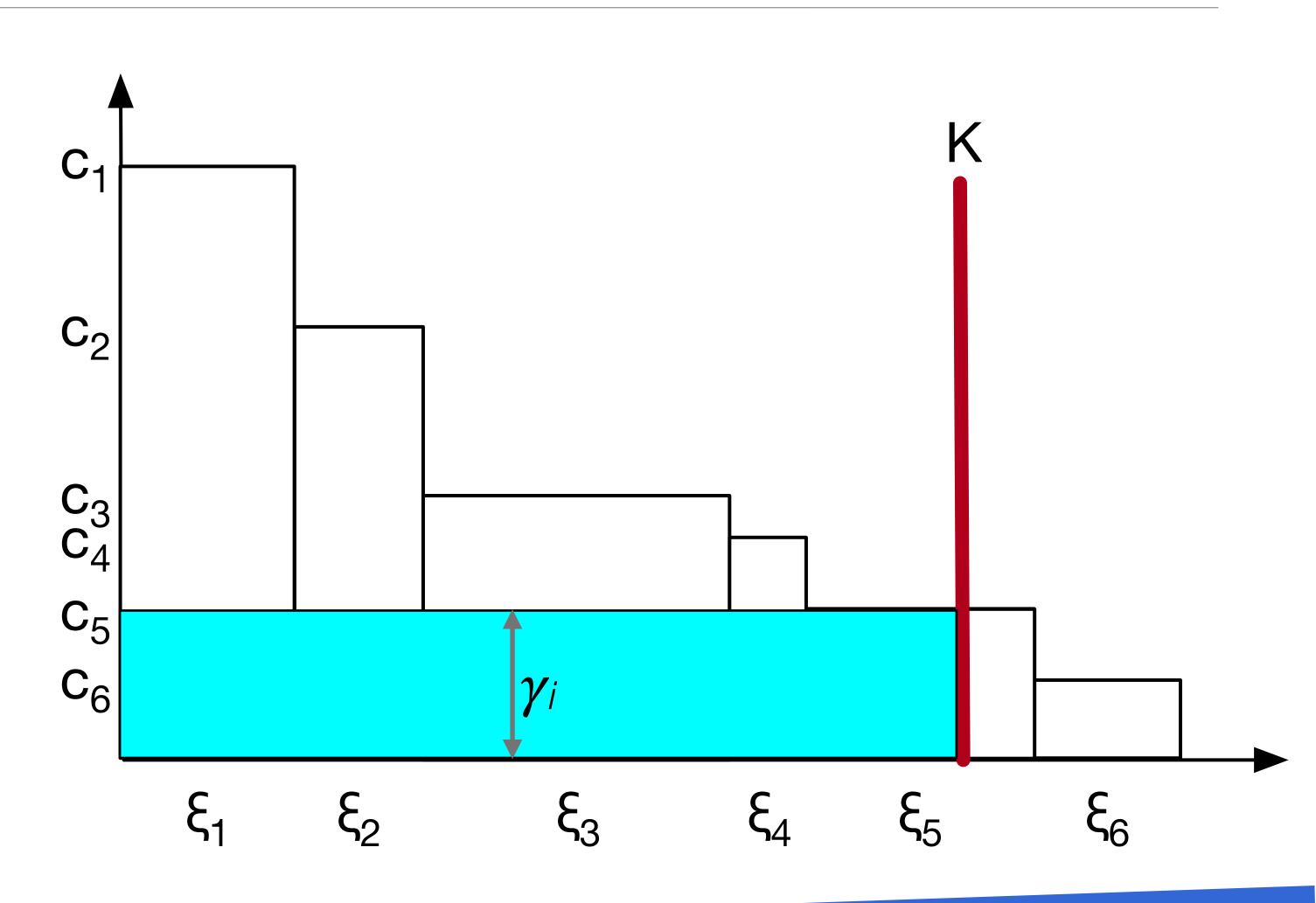
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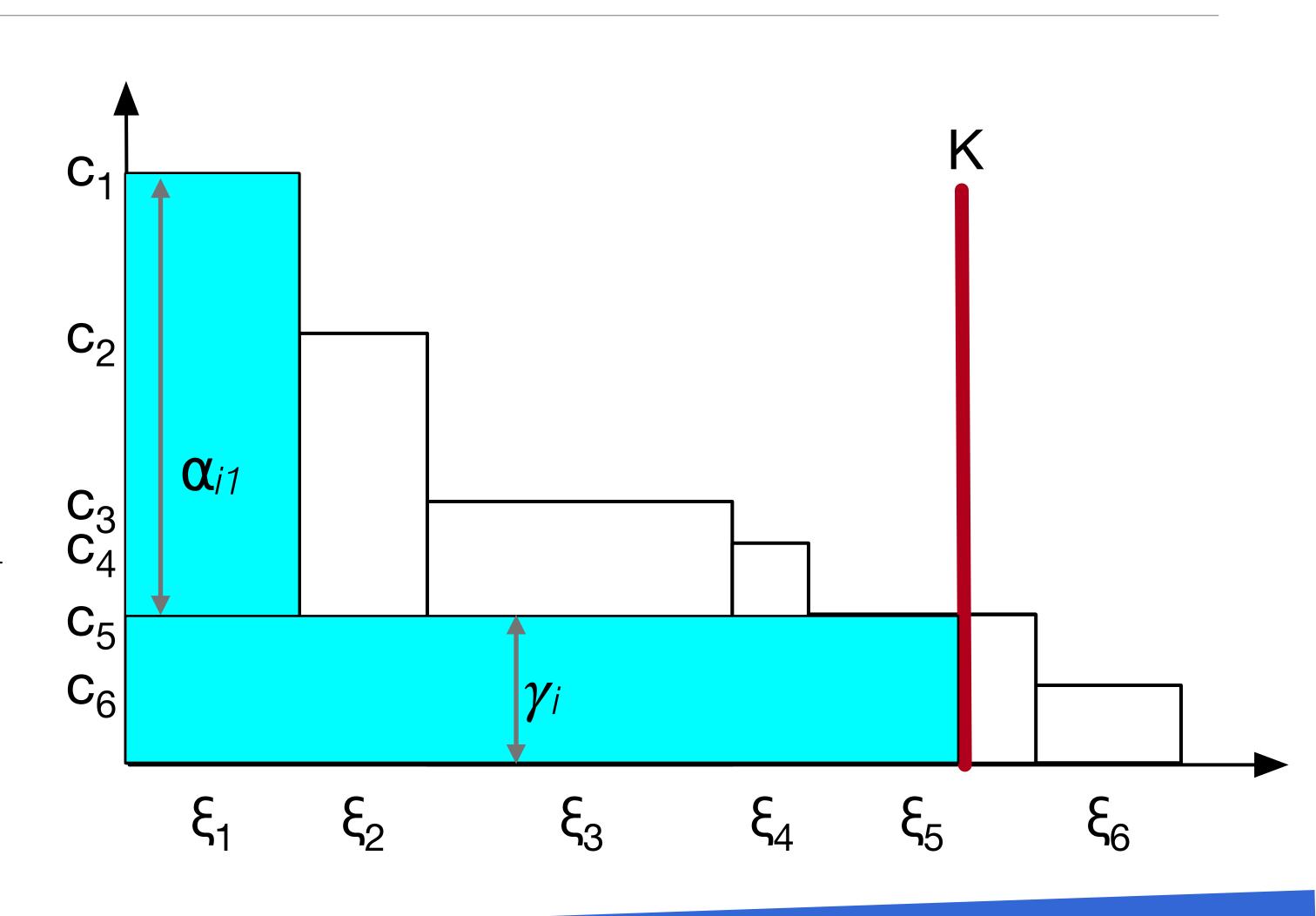
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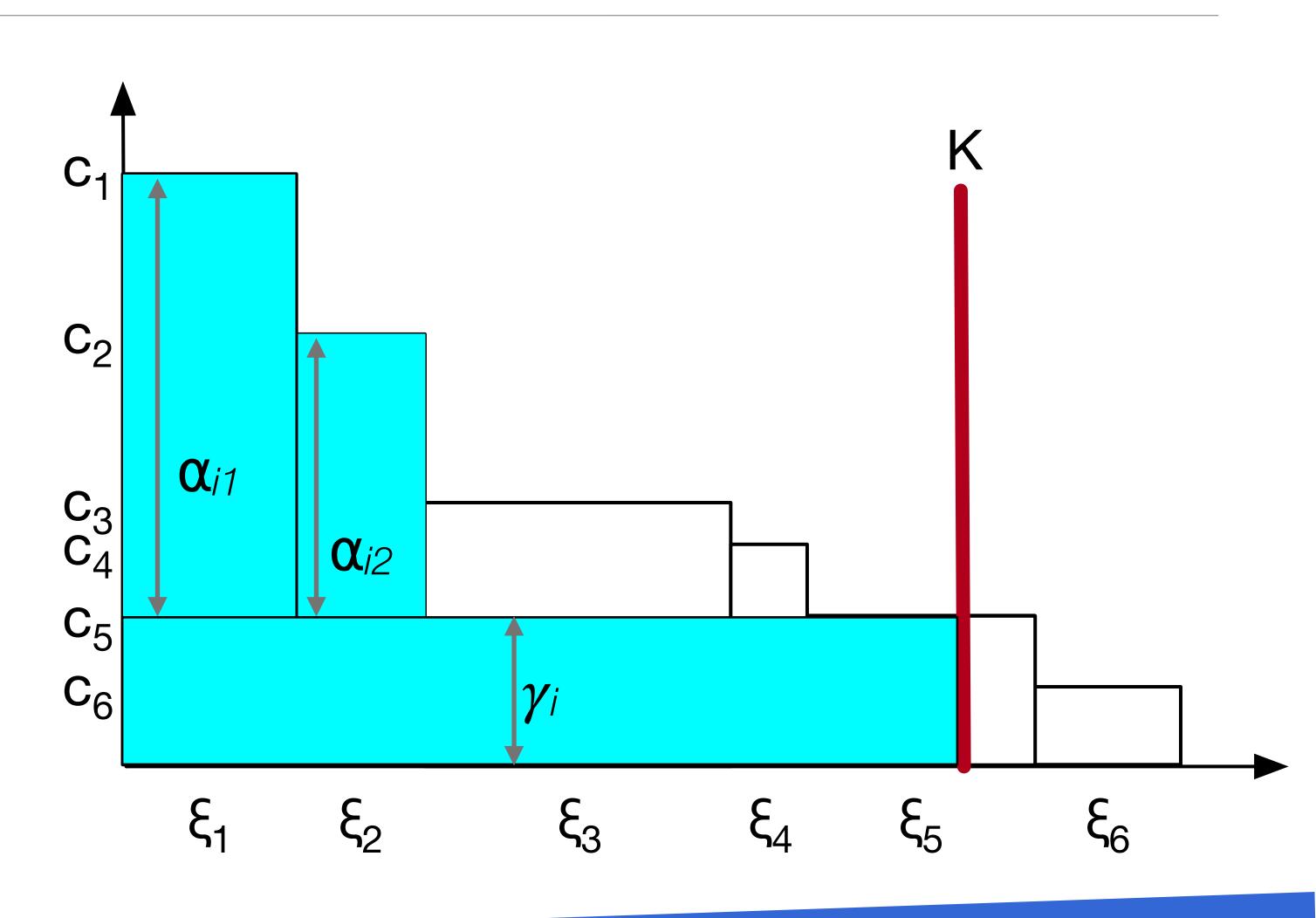
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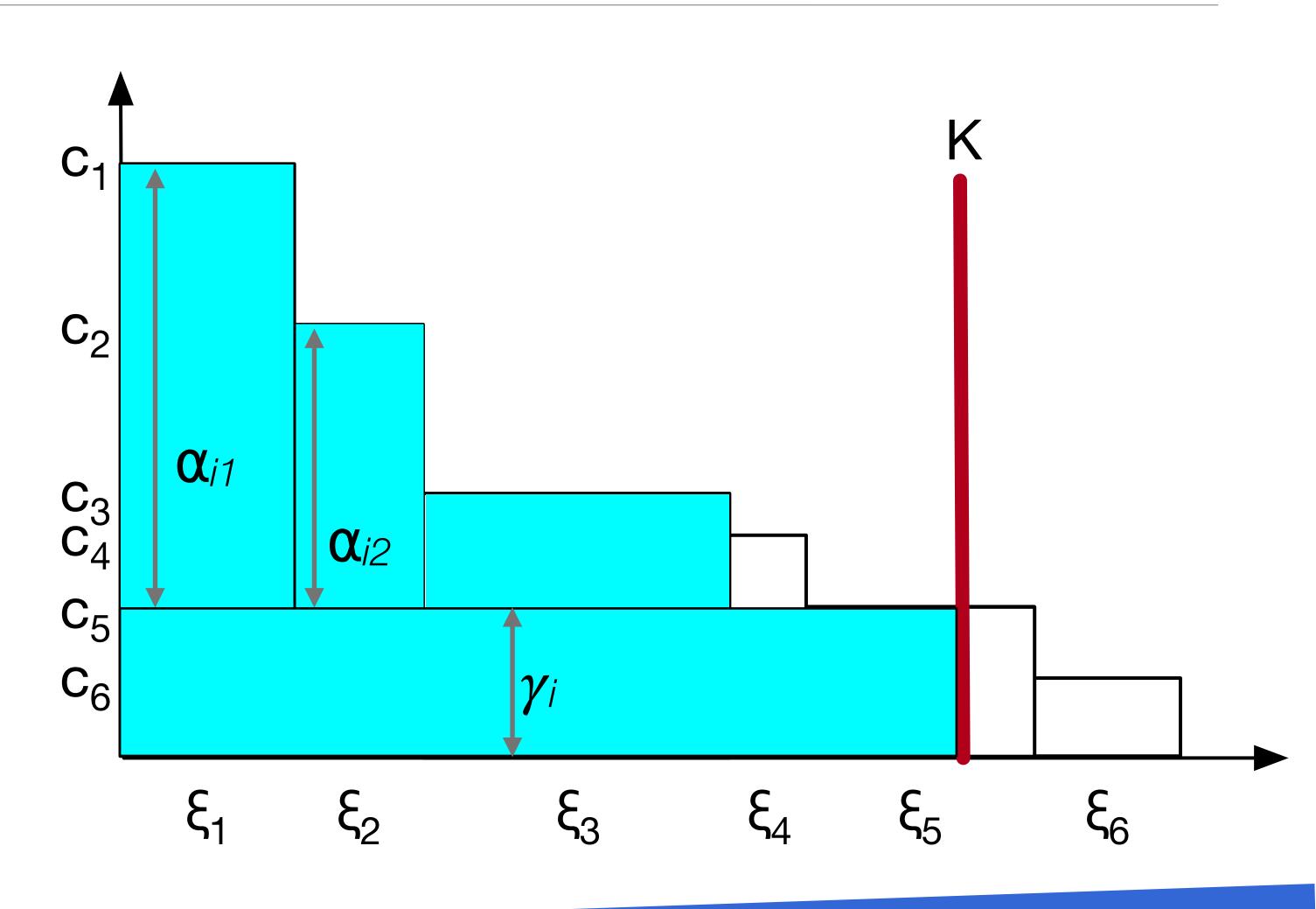
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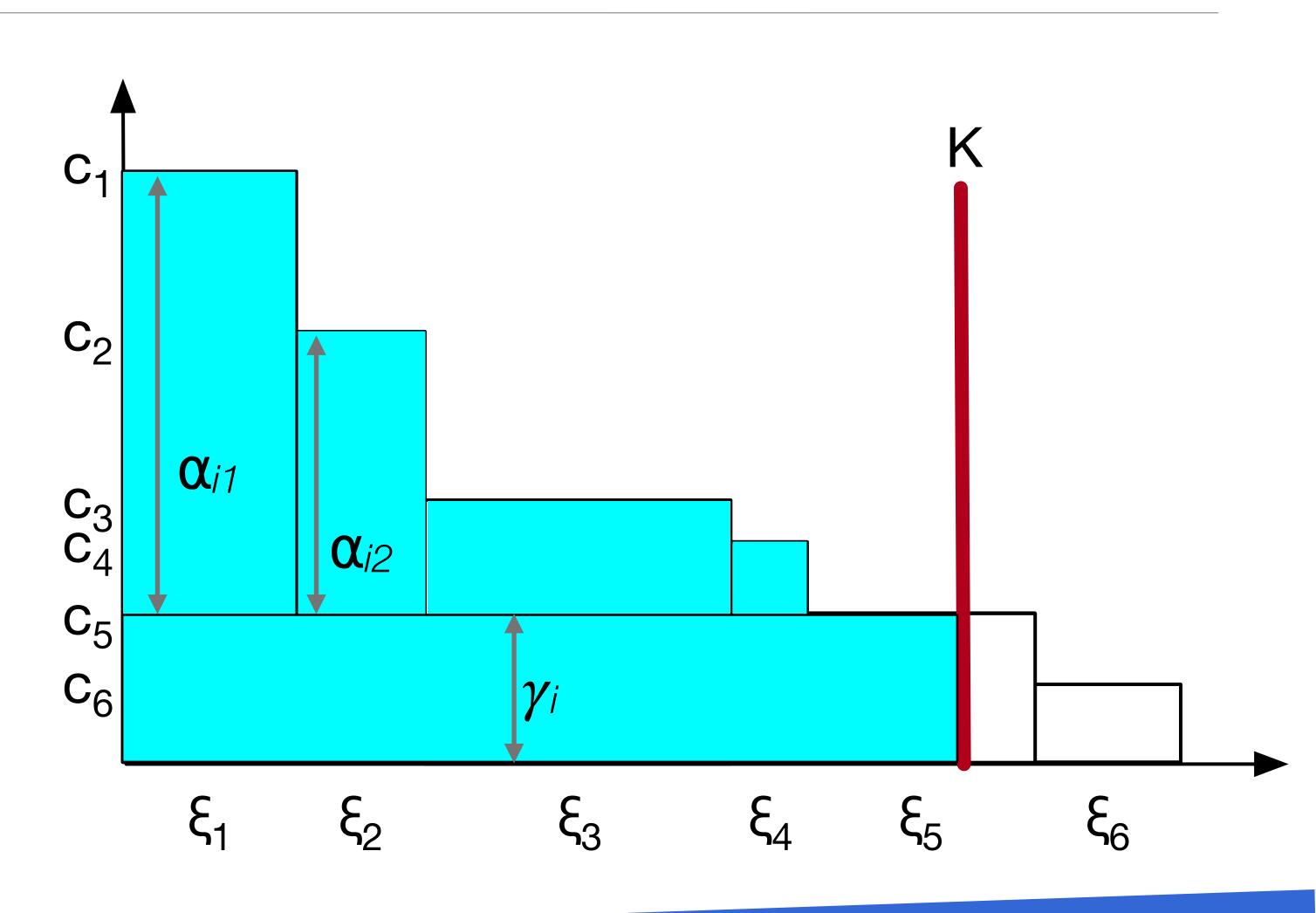
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#### Benders formulation for a discrete set of scenarios

Given a discrete set of scenarios  $s \in S$  with probability  $p_s$ , we can reformulate

$$\min_{x,y} \sum_{i \in I} f_i y_i + \sum_{i \in I} \sum_{j \in J} h_{ij} \mu_j x_{ij} - \sum_{i \in I} \sum_{s \in S} p_s \theta_s^i$$

$$(x,y) \in \mathcal{X} \qquad x,y \in \{0,1\}$$

$$\theta_s^i \leq \hat{Q}^i(x,y,\xi^s) \qquad \forall i \in I, s \in S$$

where

$$\hat{Q}^{i}(x, y, \xi^{s}) := \min_{\alpha \ge 0, \gamma \ge 0} \left\{ \sum_{j \in J} \alpha_{ij} \xi_{j} x_{ij} + \gamma_{i} K_{i} y_{i} : \alpha_{ij} + \gamma_{i} \ge c_{ij} \forall j \in J \right\}$$



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$$\hat{Q}^i (x,y,\xi^s) \leq \sum_{i \in I} \alpha_{ij}^* \xi_j x_{ij} + \gamma_i^* K_i y_i \quad \text{for any feasible dual solution } (\alpha^*,\gamma^*)$$



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and  $\hat{Q}^i(x, y, \xi^s) \le \sum_{j \in J} \alpha_{ij}^* \xi_j x_{ij} + \gamma_i^* K_i y_i$  for any feasible dual solution  $(\alpha^*, \gamma^*)$ 

in particular 
$$\hat{Q}^i(x, y, \xi^s) \leq \sum_{j \in J} \left( c_{ij} - \hat{c}_i^{\xi,*} \right)^+ \cdot \xi_j \cdot x_{ij} + \hat{c}_i^{\xi,*} \cdot K_i \cdot y_i$$

where  $\hat{c}_i^{\xi,*}$  is computed as before from any valid assignment.



#### Benders method for discrete scenarios

1.- Solve main problem 
$$\min_{x,y} \sum_{i \in I} f_i y_i + \sum_{i \in I} \sum_{j \in J} h_{ij} \mu_j x_{ij} - \sum_{i \in I} \sum_{s \in S} p_s \theta_s^i$$
 
$$(x,y) \in \mathcal{X} \quad x,y \in \{0,1\}$$

- 2.- Given incumbent solution  $(x^k, y^k)$  compute the cost of critical customer  $\hat{c}_i^{\xi^s, k}$  for each open facility i and for each scenario  $\xi^s$ .
- 3.- Add the Bender optimality cuts to the main problem

4.- Resolve main problem and iterate.



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$$\theta_s^i \leq \sum_{j \in J} \left( c_{ij} - \hat{c}_i^{\xi^s, k} \right)^+ \cdot \xi_j^s \cdot x_{ij} + \hat{c}_i^{\xi^s, k} \cdot K_i \cdot y_i$$

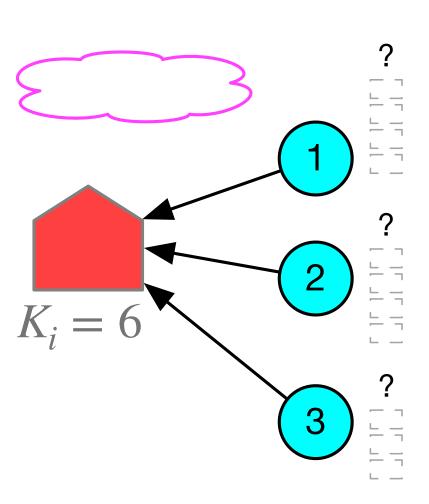
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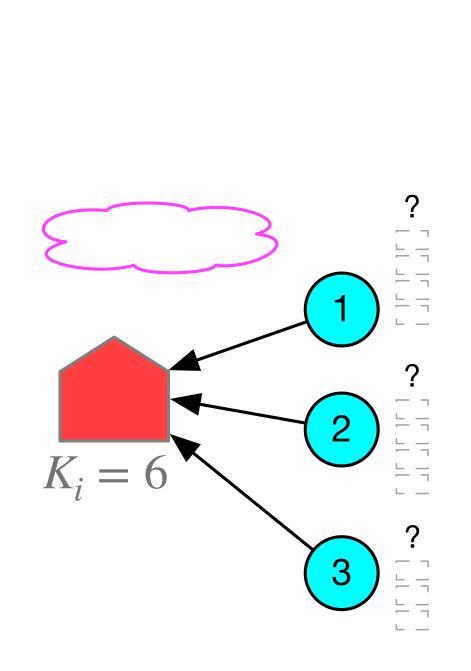
### Stochastic facility location problems with outsourcing costs

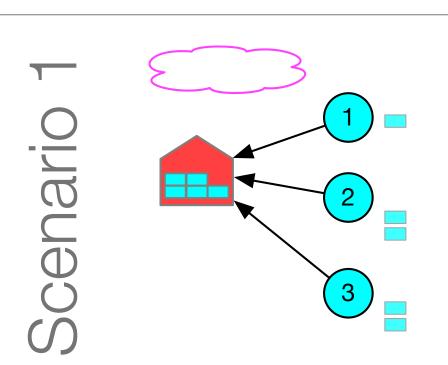
- 1. Bender formulation for a discrete set of scenarios (for example, a sample average approximation of the demand distributions)
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#### Primal solution

$$w_{i1} = 1$$

$$w_{i2} = 2$$

$$w_{i3} = 2$$

### Dual solution

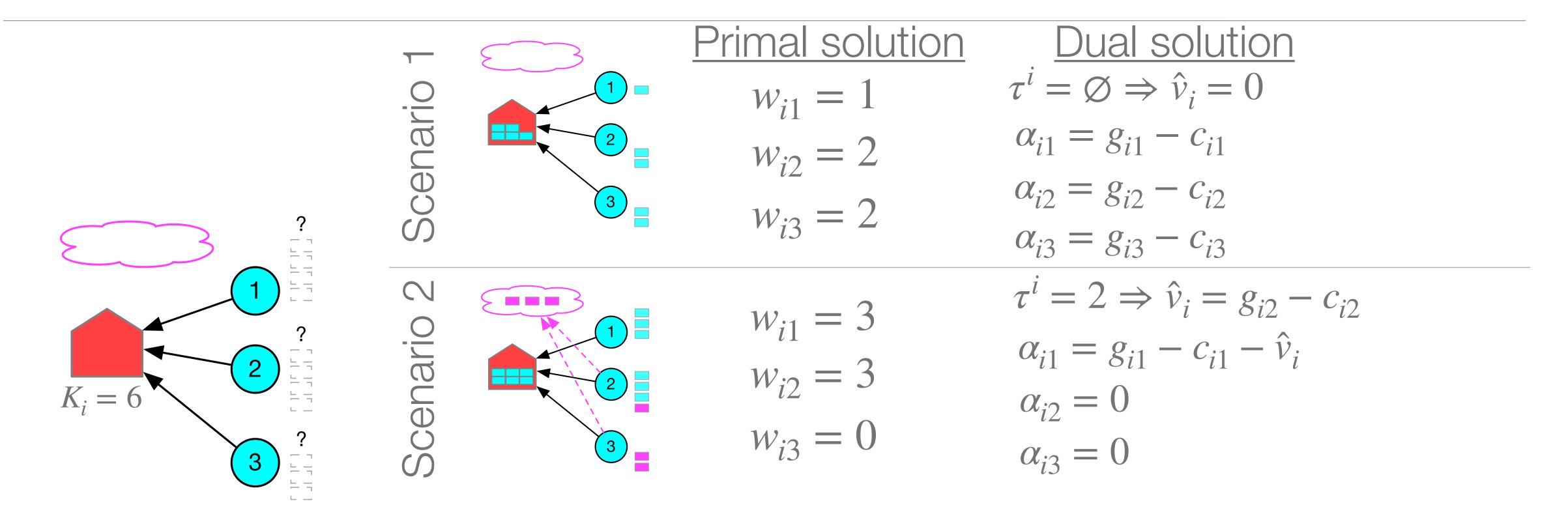
$$\tau^{i} = \varnothing \Rightarrow \hat{v}_{i} = 0$$

$$\alpha_{i1} = g_{i1} - c_{i1}$$

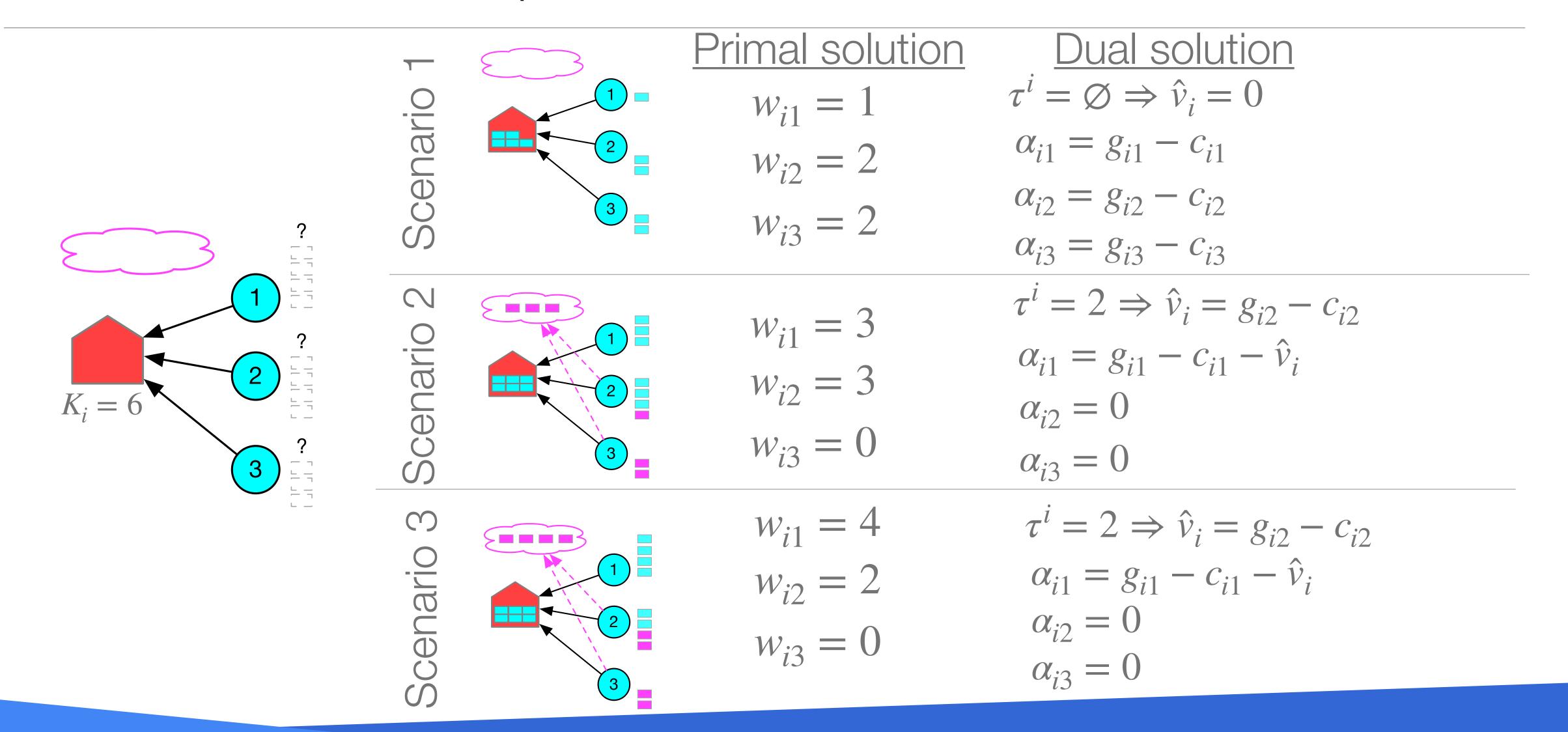
$$\alpha_{i2} = g_{i2} - c_{i2}$$

$$\alpha_{i3} = g_{i3} - c_{i3}$$



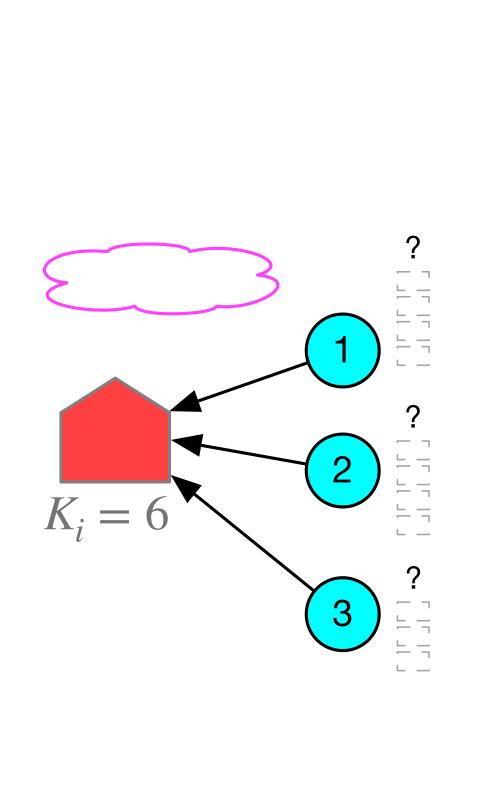


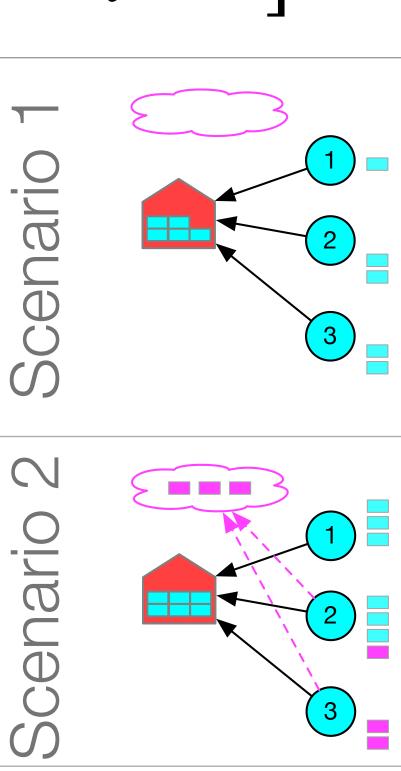




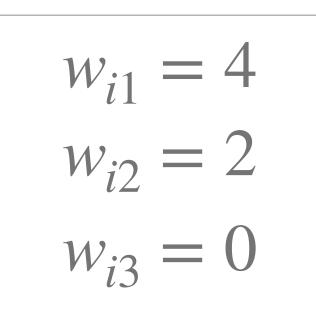


### Computing $\mathbb{E}\left[Q^{i}(x,y,\xi)\right]$





# Primal solution $w_{i1} = 1$ $w_{i2} = 2$ $w_{i3} = 2$ $w_{i3} = 3$ $w_{i2} = 3$ $w_{i3} = 3$ $w_{i4} = 3$ $w_{i5} = 3$ $w_{i2} = 3$ $w_{i5} = 3$ $w_{i6} = 3$ $w_{i7} = 3$ $w_{i1} = 3$ $w_{i1} = 3$ $w_{i1} = 3$ $w_{i2} = 3$ $w_{i2} = 3$ $w_{i3} = c_{i1}$ $\alpha_{i1} = c_{i1}$ $\alpha_{i1} = c_{i1}$ $\alpha_{i1} = c_{i1}$



 $w_{i3} = 0$ 

$$\tau^{i} = 2 \Rightarrow \hat{v}_{i} = g_{i2} - c_{i2}$$

$$\alpha_{i1} = g_{i1} - c_{i1} - \hat{v}_{i}$$

$$\alpha_{i2} = 0$$

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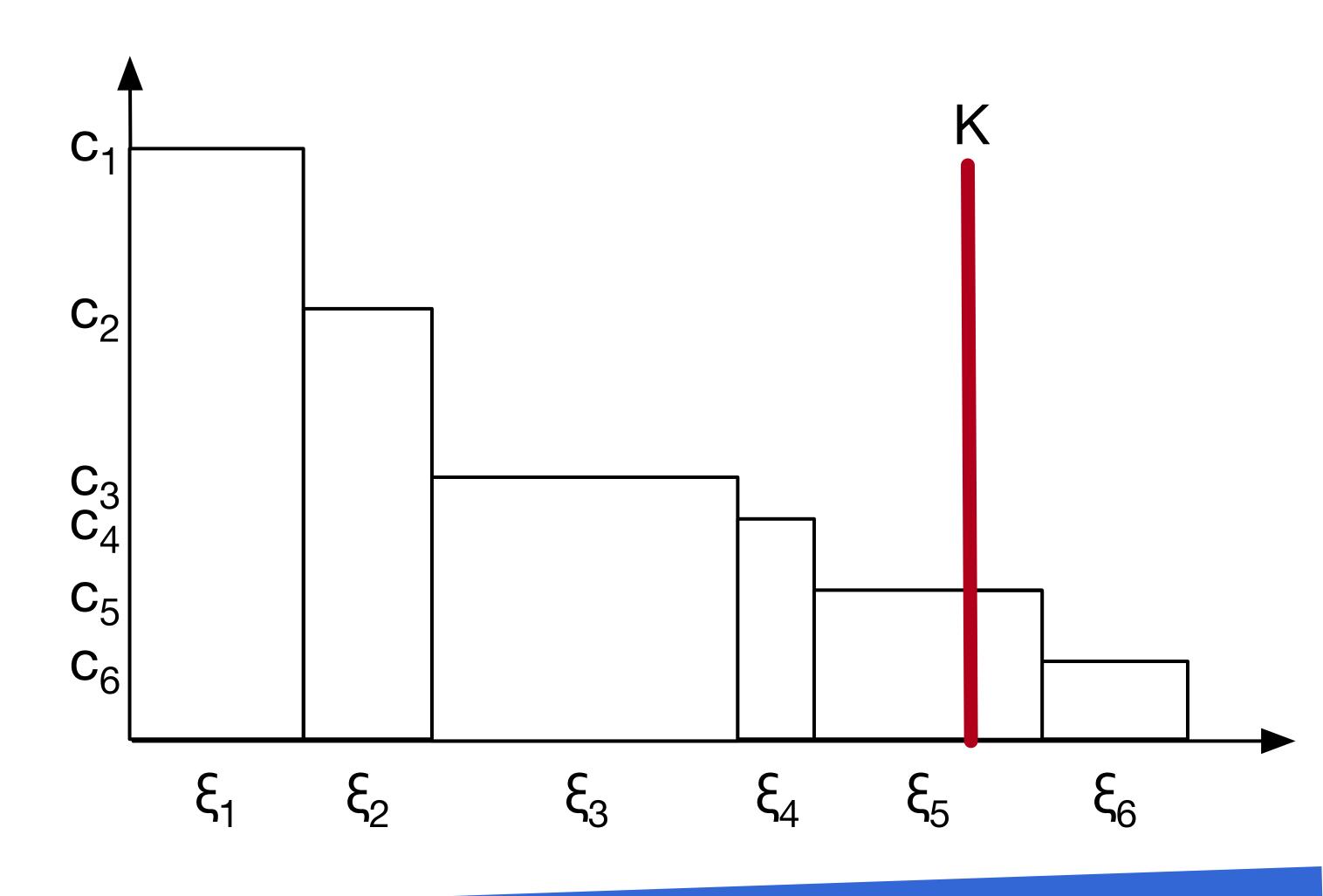
$$\alpha_{i2} = 0$$



Let  $S_j^i(x, \xi)$  be the aggregated demand of the best j customers assigned to i:

$$S_j^i(x,\xi) = \sum_{l \le j} \xi_l x_{il}$$

$$Q^{i}(x, y, \xi) = \sum_{j \in J} (c_{ij} - c_{i,j+1}) \cdot \min\{S_{j}^{i}(x, \xi), K_{i}\}$$

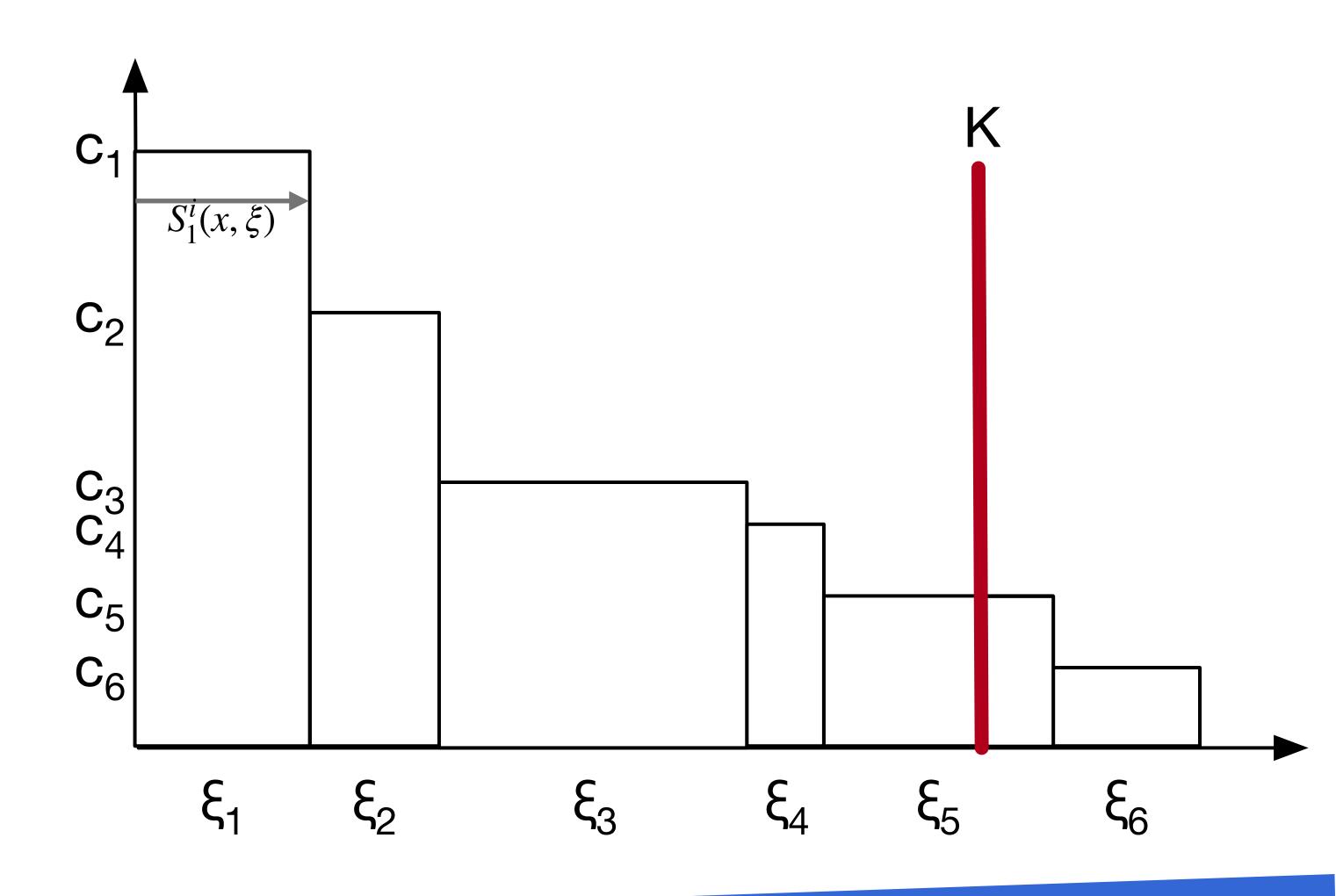




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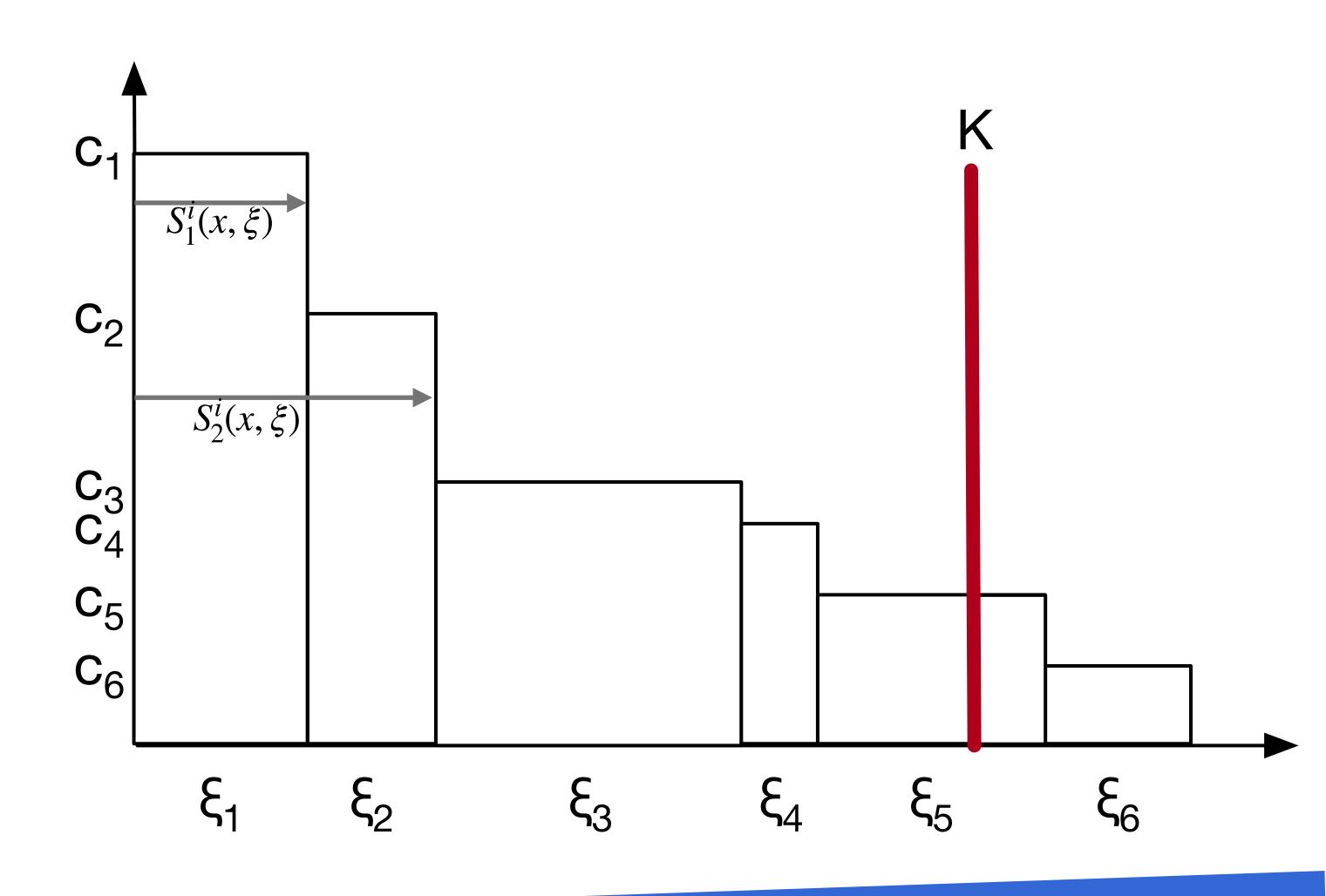




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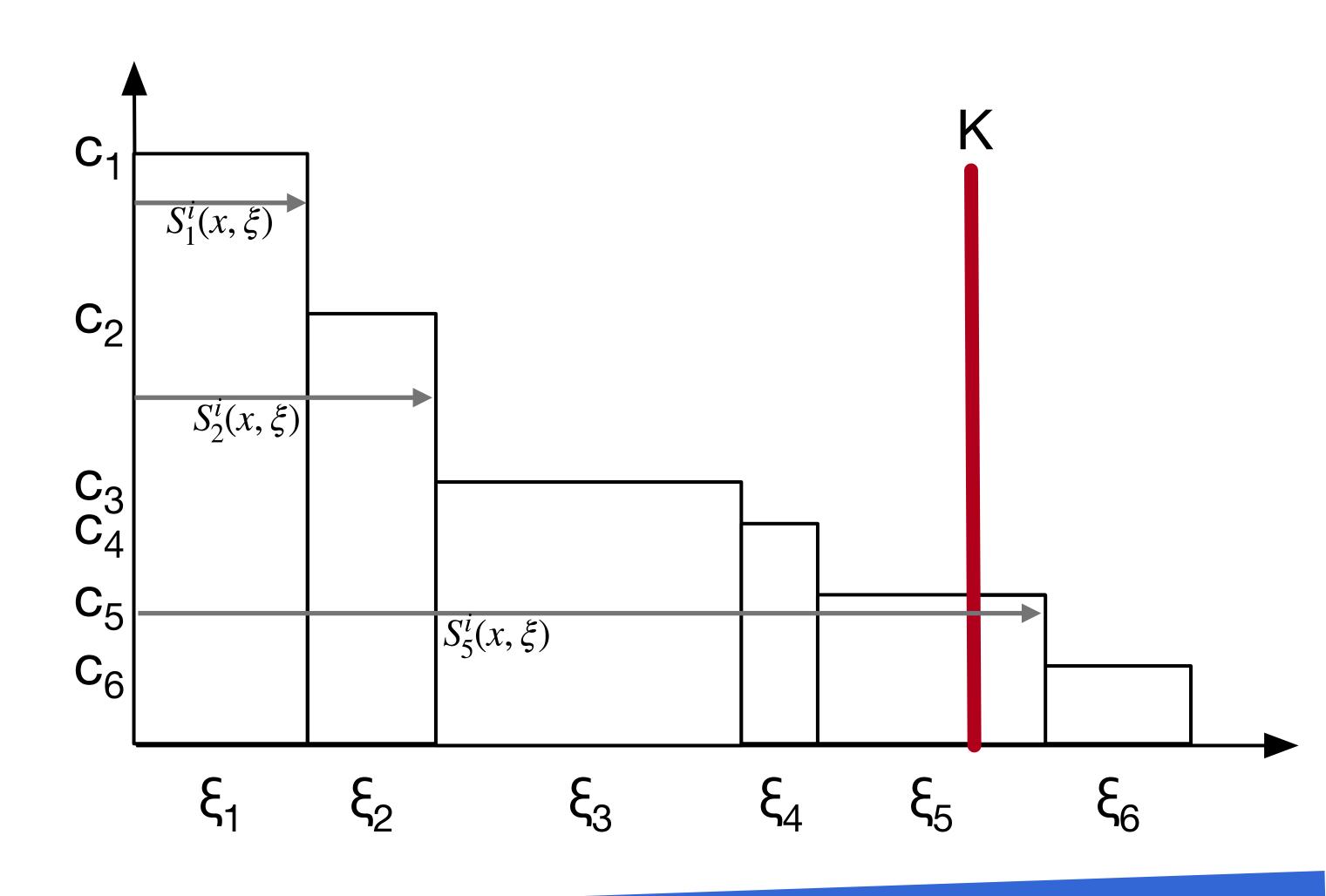




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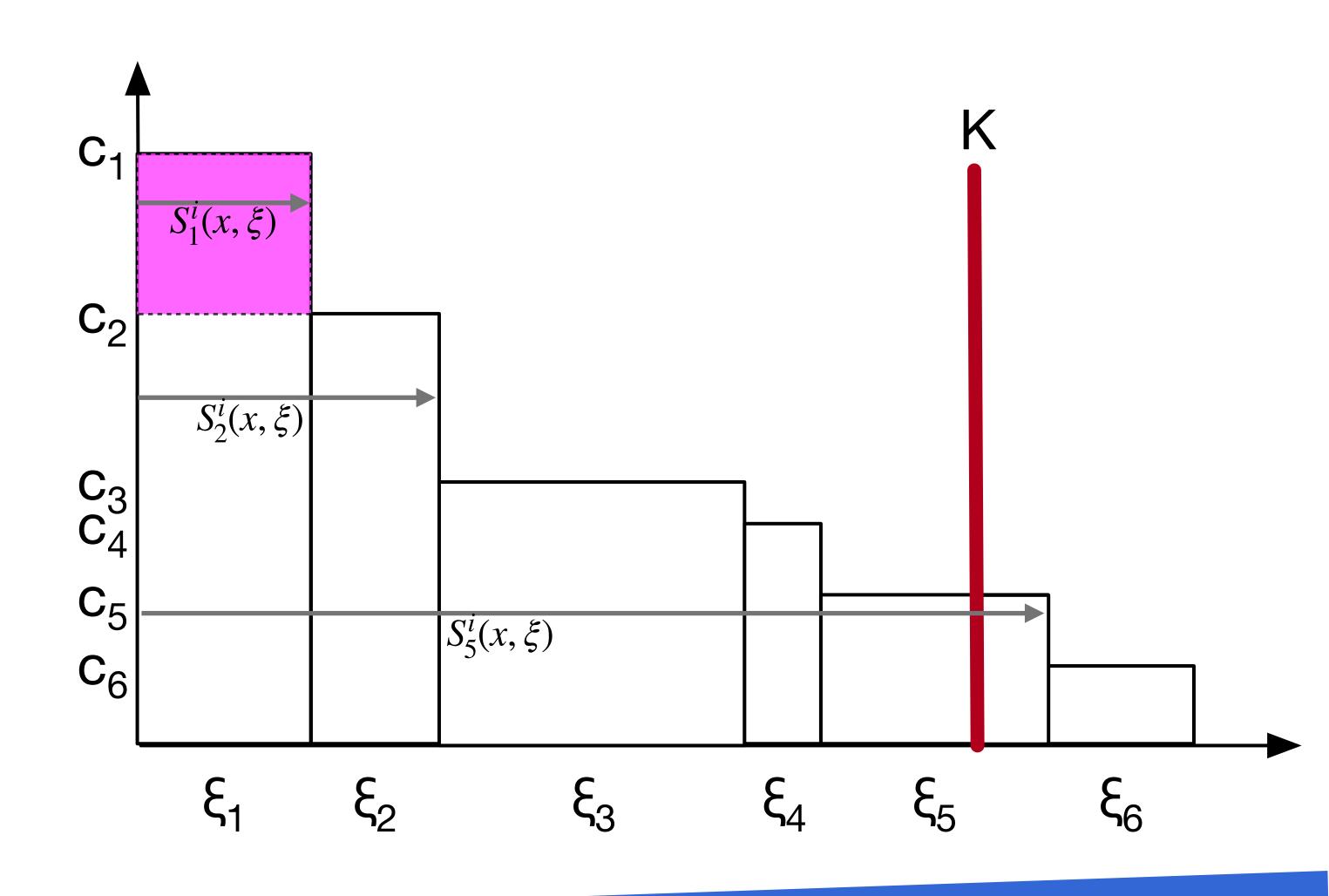




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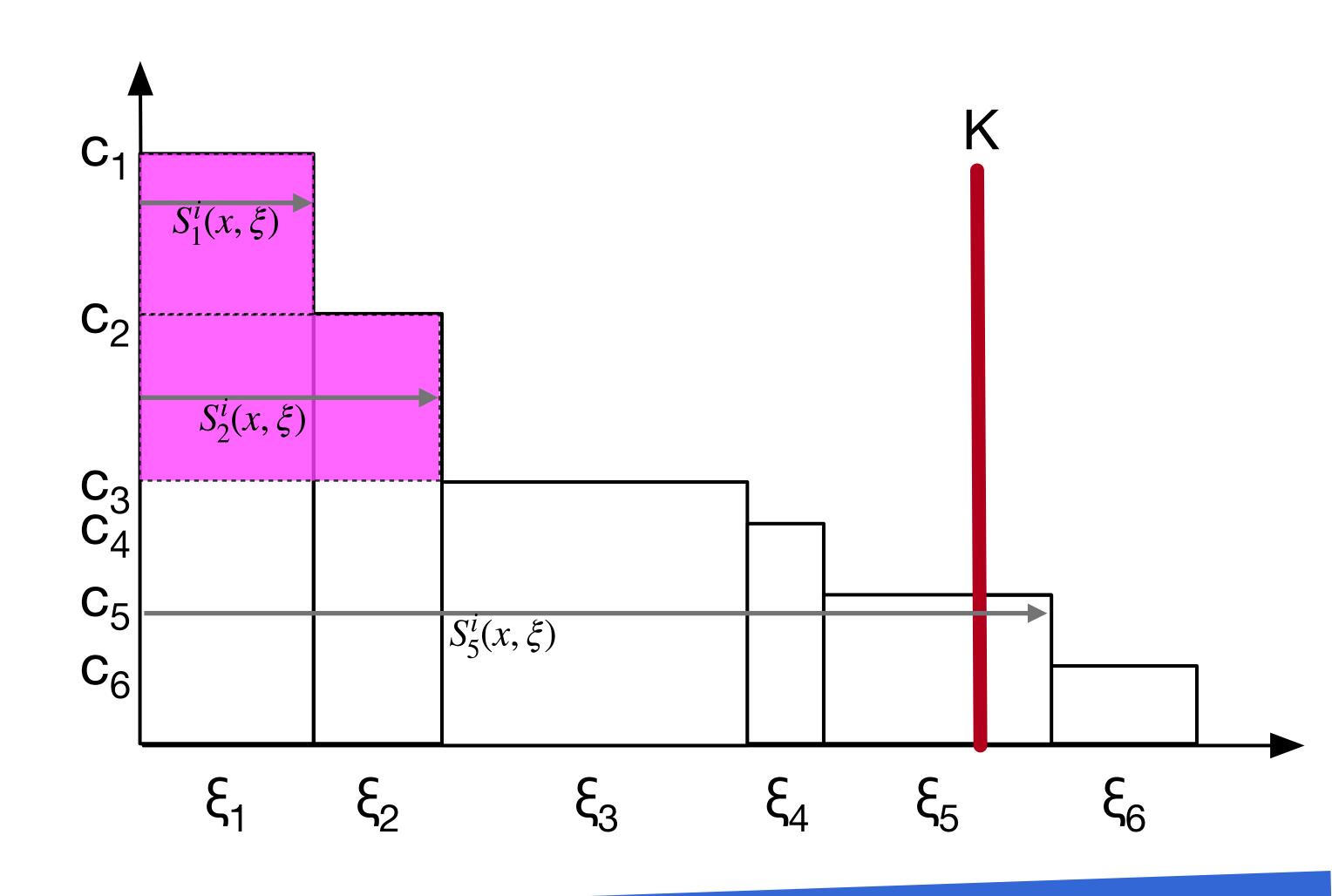




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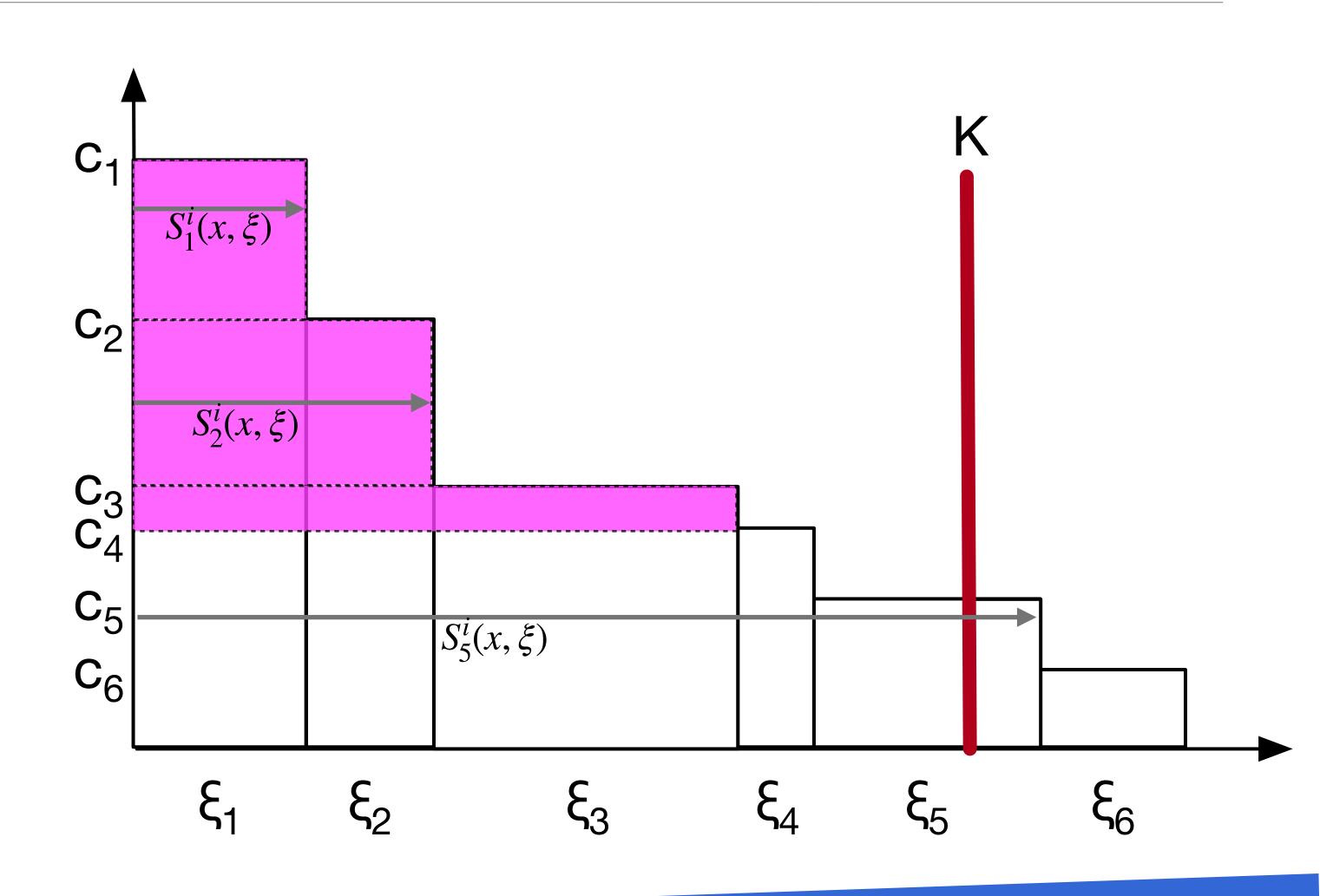




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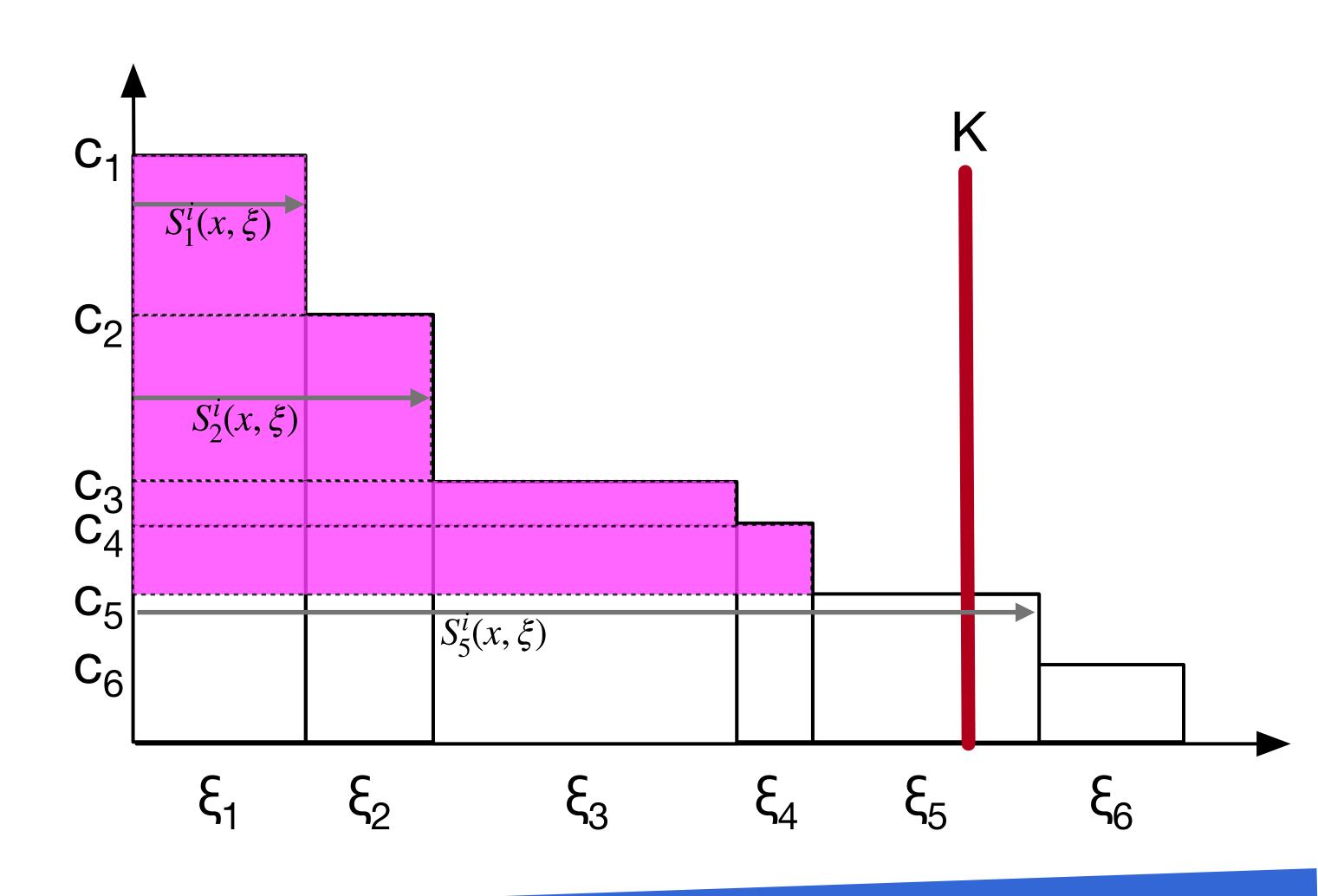




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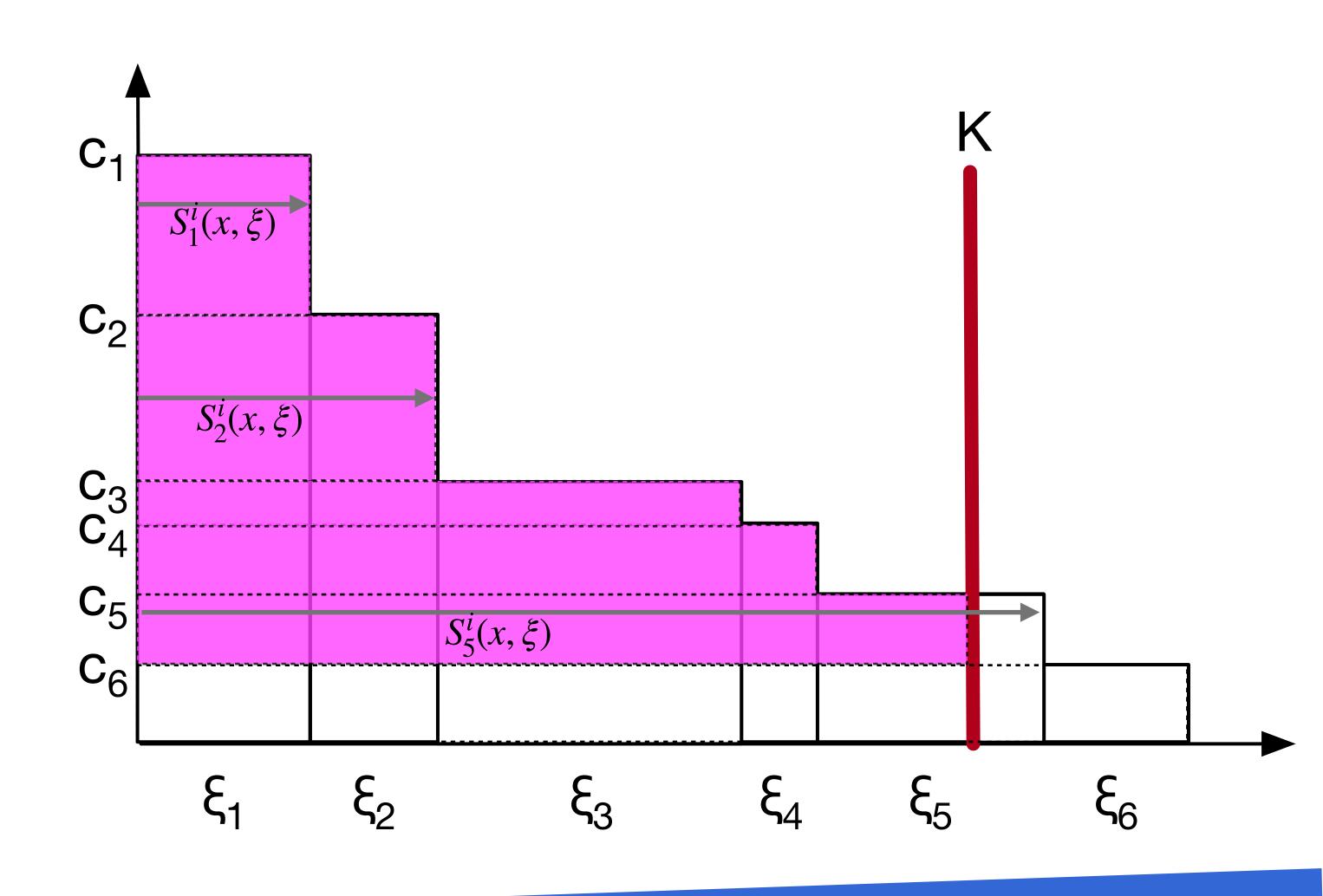




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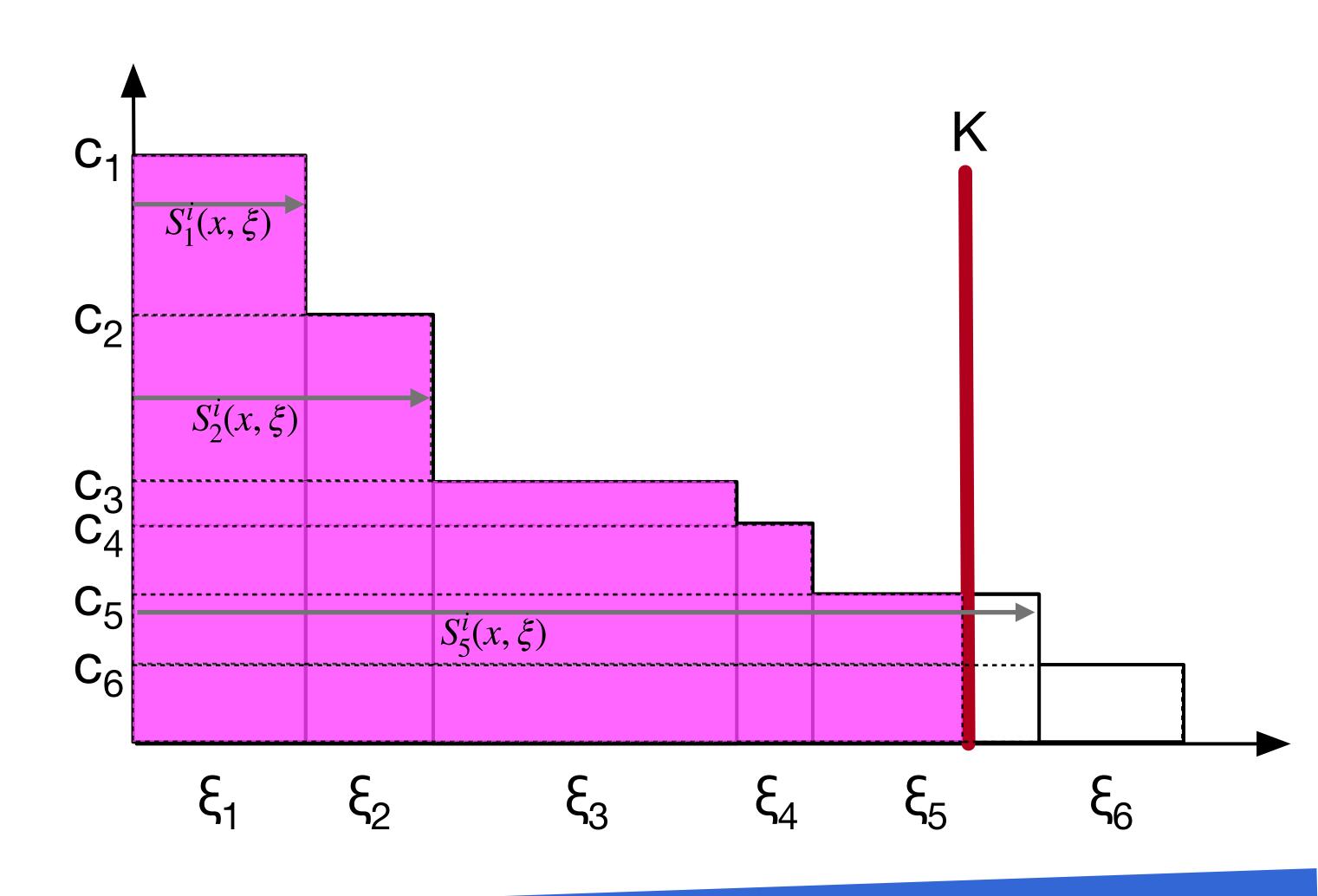




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### Expected value of the second-stage problem

For a fixed x we can obtain closed formulas for many demand distributions:

- Bernoulli distribution with mean  $\mu_j$ :  $\mathbb{E}[w_{ij}^{\xi}] = \mu_j \cdot F_{S_{j-1}}(K_i 1)$
- Poisson distribution with mean  $\mu_i$ :

$$\mathbb{E}[\min\{S_{j}(x,\xi),K_{i}\}] = K_{i} \cdot (1 - f_{Poisson(\mu_{S_{j}(x,\xi)})}(K_{i})) + (\mu_{S_{j}(x,\xi)} - K_{i}) \cdot F_{Poisson(\mu_{S_{j}(x,\xi)})}(K_{i} - 1)$$

• Exponential distribution with mean  $\mu$ :

$$\mathbb{E}[\min\{S_{j}(x,\xi),K_{i}\}] = j \cdot \mu \cdot F_{Gamma(j+1,1/\mu)}(K_{i}) + K_{i}\left(1 - F_{Gamma(j,1/\mu)}(K_{i})\right)$$



#### Benders formulation for a discrete set of scenarios

Main problem

$$\min_{x,y} \left\{ \sum_{i \in I} f_i y_i + \sum_{i \in I} \sum_{j \in J} h_{ij} \mu_j x_{ij} - \sum_{i \in I} \mathbb{E} \left[ Q^i(x,y,\xi) \right] : (x,y) \in \mathcal{X} \right\}$$

$$\min_{x,y} \left\{ \sum_{i \in I} f_i y_i + \sum_{i \in I} \sum_{j \in J} h_{ij} \mu_j x_{ij} - \sum_{i \in I} \sum_{j \in J} \left( c_{i,\sigma^i(j)} - c_{i,\sigma^i(j+1)} \right) \cdot \mathbb{E} \left[ \min \{ S^i_j(x,\xi), K_i \} \right] : (x,y) \in \mathcal{X} \right\}$$



By the law of total probabilities:

$$\mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\right] = \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\cdot 1_{S_{j}^{i}(x,\xi)\leq K_{i}}\right] + \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\cdot 1_{S_{j}^{i}(x,\xi)>K_{i}}\right]$$

$$S_j^i(x,\xi) = \sum_{l \le j} \xi_l x_{il}$$



By the law of total probabilities:

$$\begin{split} \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\right] &= \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\cdot 1_{S_{j}^{i}(x,\xi)\leq K_{i}}\right] + \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\cdot 1_{S_{j}^{i}(x,\xi)>K_{i}}\right] \\ &= \mathbb{E}\left[S_{j}^{i}(x,\xi)\cdot 1_{S_{j}^{i}(x,\xi)\leq K_{i}}\right] + \mathbb{E}\left[K_{i}\cdot 1_{S_{j}^{i}(x,\xi)>K_{i}}\right] \end{split}$$

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$$S_j^i(x,\xi) = \sum_{l \le j} \xi_l x_i$$

Non-linear function because coefficients also depends on  $\boldsymbol{x}$ 



But we can use another first-stage assignment x' too

$$\begin{split} \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\right] &= \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\cdot 1_{S_{j}^{i}(\mathbf{x}',\xi)\leq K_{i}}\right] + \mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\cdot 1_{S_{j}^{i}(\mathbf{x}',\xi)>K_{i}}\right] \\ &\leq \mathbb{E}\left[S_{j}^{i}(x,\xi)\cdot 1_{S_{j}^{i}(\mathbf{x}',\xi)\leq K_{i}}\right] + \mathbb{E}\left[K_{i}\cdot 1_{S_{j}^{i}(\mathbf{x}',\xi)>K_{i}}\right] \\ &= \sum_{l\leq i}\mathbb{E}\left[\xi_{l}\cdot 1_{S_{j}^{i}(\mathbf{x}',\xi)\leq K_{i}}\right]\cdot x_{il} + K_{i}\cdot \mathbb{P}\left[S_{j}^{i}(\mathbf{x}',\xi)>K_{i}\right] \end{split}$$

Linear upper bound for a fixed x'

$$S_j^i(x,\xi) = \sum_{l \le j} \xi_l x_{il}$$



Lemma: 
$$\mathbb{E}\left[\min\{S_j^i(x,\xi),K_i\}\right]$$
 is a concave function at  $x$  and

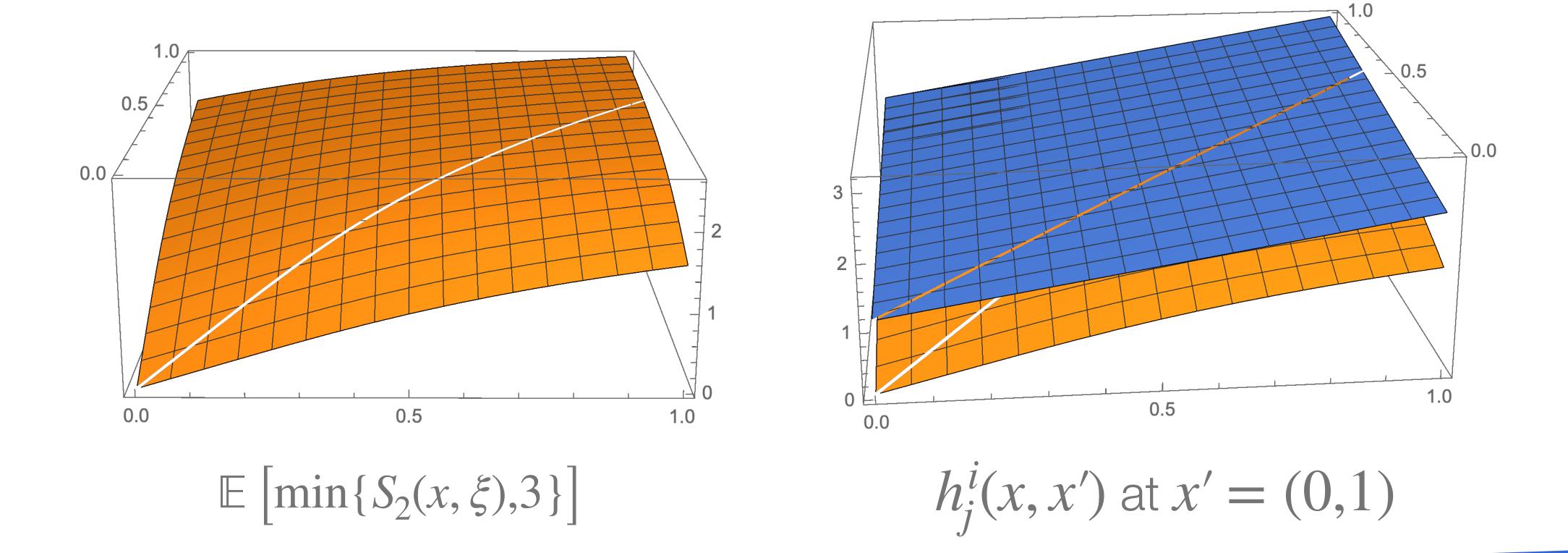
$$h_j^i(x, x') := \sum_{l \le j} \mathbb{E} \left[ \xi_l \cdot 1_{S_j^i(\mathbf{x}', \xi) \le K_i} \right] \cdot x_{il} + K_i \cdot \mathbb{P} \left[ S_j^i(\mathbf{x}', \xi) > K_i \right]$$

is in its subdifferential at x'



### Example:

Two demands  $\xi_1 \rightsquigarrow \exp(1/2)$  and  $\xi_2 \rightsquigarrow \exp(1/3)$  with K=3





### Benders formulation for general distributions

We add a variable  $z_{ij} \geq 0$  which correspond to the value of  $\mathbb{E}\left[\min\{S_j^i(x,\xi),K_i\}\right]$ 

$$\min_{x,y,z} \sum_{i \in I} f_i y_i + \sum_{i \in I} \sum_{j \in J} g_{ij} \mu_j x_{ij} - \sum_{i \in I} \sum_{j \in J} (c_{i,\sigma^i(j)} - c_{i,\sigma^i(j+1)}) z_{ij}$$

$$(x,y) \in \mathcal{X} \qquad x,y \in \{0,1\}$$

It can be solve by iteratively adding Generalized Benders optimality cuts for the given incumbent solution (x', y')

$$z_{ij} \leq \sum_{l \leq j} \mathbb{E} \left[ \xi_l \cdot 1_{S_j^i(x',\xi) \leq K_i y_i'} \right] \cdot x_{il} + K_i \cdot y_i \cdot \mathbb{P} \left[ S_j^i(x',\xi) > K_i y_i' \right]$$



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Valid constraints on  $z_{ij}$  variables.  $\left(z_{ij} \approx \mathbb{E}\left[\min\{S_j^i(x,\xi),K_i\}\right]\right)$ 

$$\left(z_{ij} \approx \mathbb{E}\left[\min\{S_j^i(x,\xi),K_i\}\right]\right)$$

$$\mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\right] \leq \mathbb{E}\left[S_{j}^{i}(x,\xi)\right] \quad \Rightarrow \quad z_{ij} \leq \sum_{l \in J:\sigma^{i}(l) \leq \sigma^{i}(j)} \mathbb{E}[\xi_{l}]x_{il}$$

$$\mathbb{E}\left[\min\{S_{j}^{i}(x,\xi),K_{i}\}\right] \leq K_{i} \quad \Rightarrow \quad z_{ij} \leq K_{i}y_{i}$$

$$S_{j}^{i}(x,\xi) = S_{j-1}^{i}(x,\xi) + \xi_{j}x_{ij} \quad \Rightarrow \quad z_{ij} \leq z_{i,j-1}$$

$$z_{ij} \leq z_{i,j-1} + \mathbb{E}[\xi_{j}]x_{ij}$$



### Submodularity of $\mathbb{E}\left[\min\{S_j^i(x,\xi),K_i\}\right]$

A set-valued function is sub modular if it has "diminishing returns".

- Lemma: Set-valued function  $\mu(A) := \min\{S_j(1_A, \xi), K_i y_i\}$  is submodular for a given  $x, y, \xi$ .
- . Corollary: Set-valued function  $\mu'(A) := \mathbb{E}\left[\min\{S_j(1_A,\xi),K_iy_i\}\right]$  is submodular for a given x,y.



### Submodularity of $\mathbb{E}\left[\min\{S_j^i(x,\xi),K_i\}\right]$

Since 
$$\mathbb{E}\left[\min\{S_j^i(x,\xi),K_i\}\right]$$
 is submodular, we can add submodular cuts (\*)

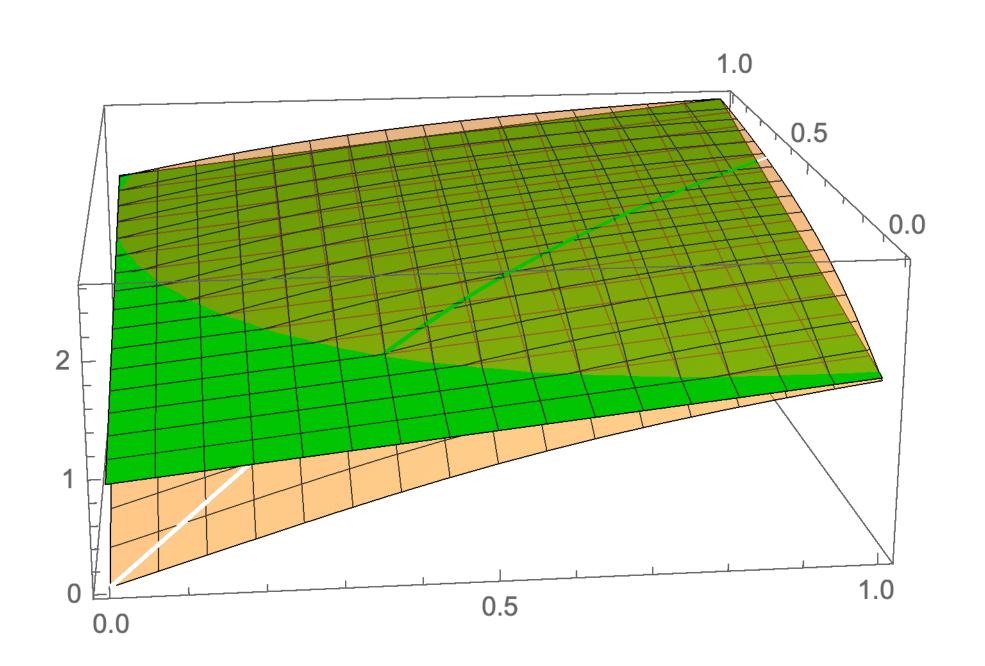
$$\begin{split} z_{ij} & \leq \mathbb{E}[\min\{S_{j}(x'), K_{i}y_{i}\}] \cdot y_{i} + \sum_{l: x'_{il} = 0} \mathbb{E}[\xi_{l}1_{S_{j}(x') + \xi_{l} \leq K_{i}} + (K_{i} - S_{j}(x'))1_{S_{j}(x') \leq K_{i} \leq S_{j}(x') + \xi_{l}}] \cdot x_{il} \\ & - \sum_{l: x'_{il} = 1} \mathbb{E}[\xi_{l}1_{S_{j} \leq K_{i}} + (K_{i} - (S_{j} - \xi_{l}))1_{S_{j} - \xi_{l} \leq K_{i} \leq S_{j}}] \cdot (1 - x_{il}) \end{split}$$

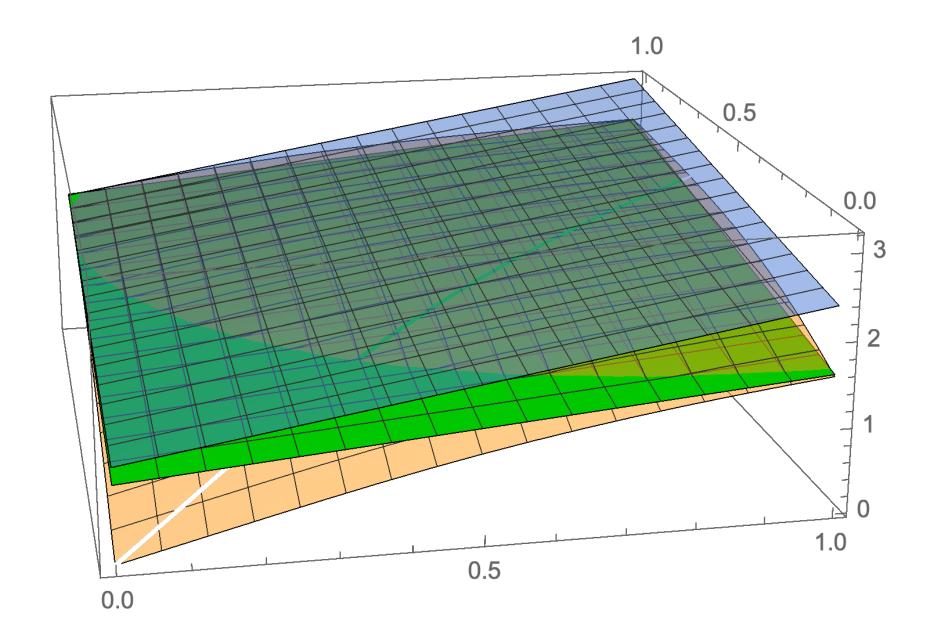
(\*) see Nemhauser & Wolsey (1981), Ljubic & M. (2018)



### Example:

Two demands  $\xi_1 \rightsquigarrow \exp(1/2)$  and  $\xi_2 \rightsquigarrow \exp(1/3)$  with K=3





Submodular cut at x' = (0,1)



### Piecewise linear upper bound for fractional solutions.

Both Bender and submodular cuts <u>requires an integer solution</u> x' to compute the coefficients to generate a cut. Can we create cuts for the relaxation of the problem?

If  $\sum_{l \in J: \sigma^i(l) < \sigma^i(i)} x_{ij} = \kappa \in \mathbb{N}$ , we can consider to sum the  $\kappa$  "worst" customers.

**Proposition**: Assume that random demands can be ordered in the usual stochastic order  $\xi_{(1)} \geq_{st} \xi_{(2)} \geq_{st} \dots \xi_{(j)}$ . Then

$$\mathbb{E}\left[\min\{S_{j}(x), K_{i}y_{i}\}\right] \leq \mathbb{E}\left[\min\left\{\sum_{l=1}^{\kappa} \xi_{(l)}, K_{i}y_{i}\right\}\right]$$



### Piecewise linear upper bound for fractional solutions.

Let  $B_{ij}(\kappa) := \mathbb{E}[\min\{\mathcal{S}_{\kappa}, K_i y_i\}]$  the expected value considering the "worst"  $\kappa$  customer. We can extend this function using a piece-wise linear function, creating the valid upper bound:

$$z_{ij} \leq B_{ij}(\kappa) + (B_{ij}(\kappa+1) - B_{ij}(\kappa)) \cdot \left( \sum_{l \in J: \sigma^i(l) \leq \sigma^i(j)} x_{il} - \kappa \right)$$

- For i.i.d. demand distributions,  $\mathcal{S}_{\kappa}$  is the sum of  $\kappa$  random variables. The bound is tight.
- For single-parameter distribution (e.g. exponential or Poisson) the  $\kappa$  worst customers are the one with higher expected demand. The bound is not tight.



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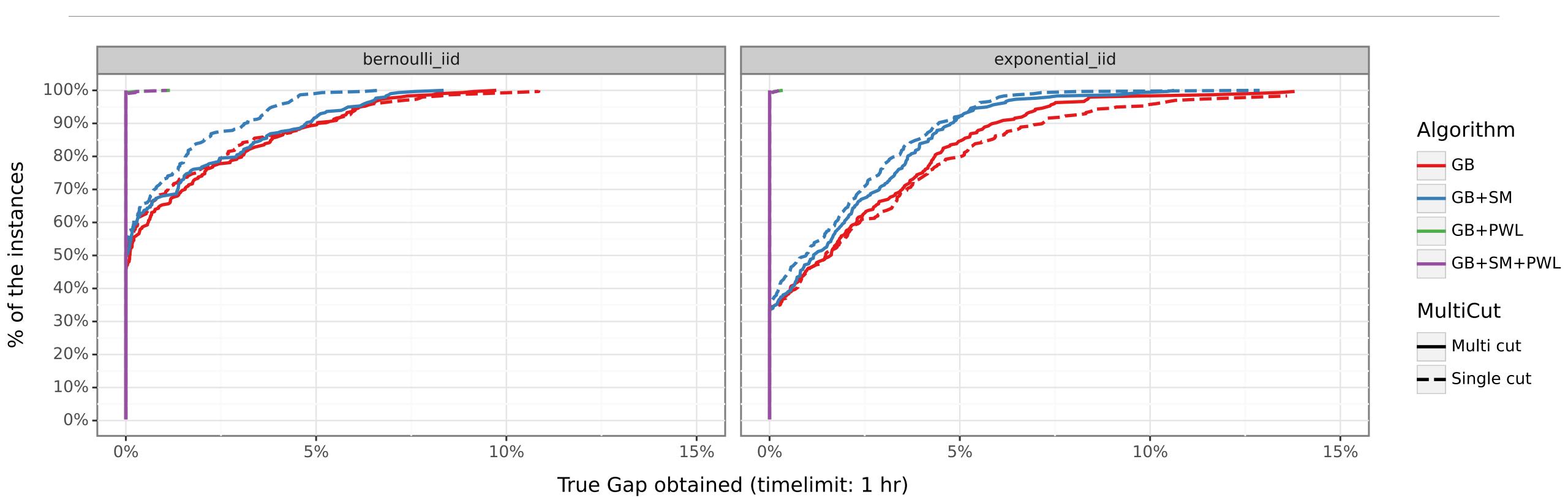
### Computational experiments

### Dataset for benchmarking:

- Albareda-Sambola et al (2011). 297 instances based on TSP problems, with 15 facilities and 30 customers.
- Random demands with Bernoulli and Exponential distributions with mean value 0.1, 0.5 or 0.9.
- Comparison of Benders, Submodular and PWL cuts using multi-cut (one cut for each  $z_{ii}$ ) or a single-cut (aggregated cut for each facility).
- Coded in C++ using Gurobi as solver.



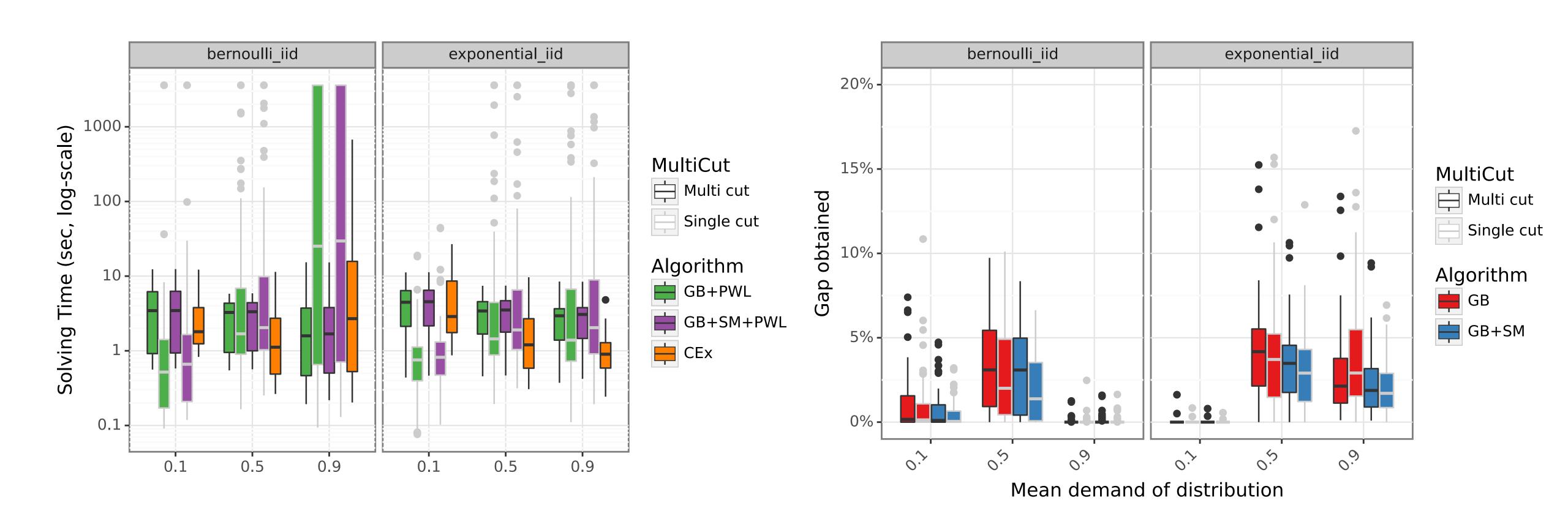
### Performance profile for i.i.d. demands



- Adding PWL cuts solved all problems in a few seconds
- 50%/40% of instances are solved up to optimality. ~80% with <5% gap.

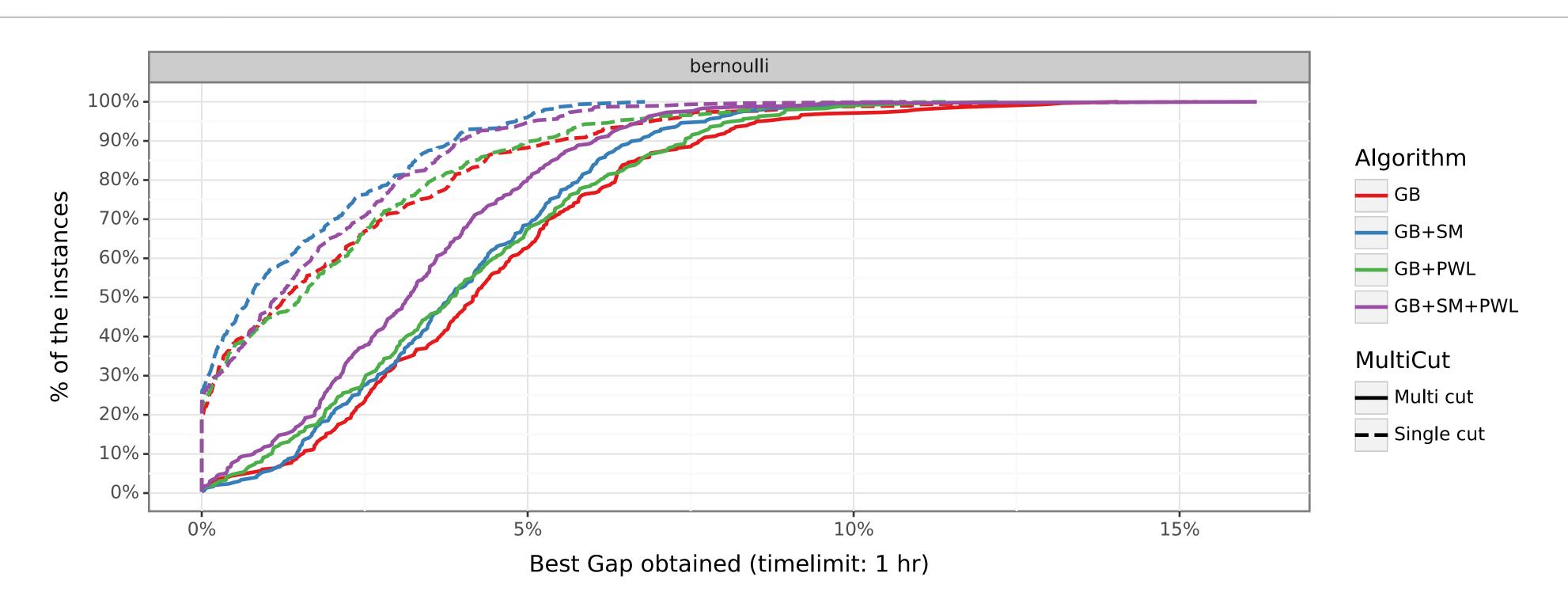


### Performance profile for i.i.d. demands





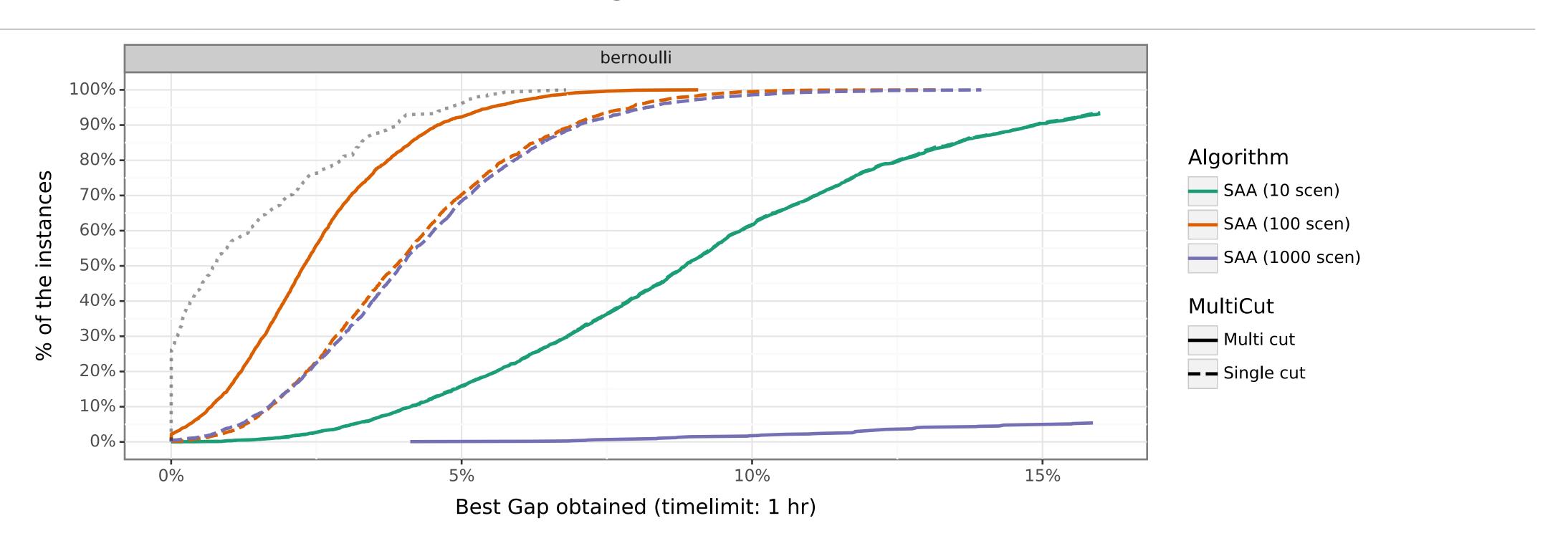
### Performance profile for non-i.i.d. demands



- Too many cuts. Aggregating cuts performs better.
- PWL cuts are not longer efficient. Submodular cuts improve the performance
- Still > 90% of instances solved with <5% gap.



### Comparison with sample average approximation



- SAA with 10 scenarios is solved up to optimality, but solution quality is very bad.
- Adding more scenarios improves the quality but became harder to solve.
- Generalized Bender outperforms SAA, particularly for smaller gaps.



#### Conclusions

- Benders methodology for two-stage assignment problem where the second stage is a stochastic knapsack problem
  - An exact solution to the problem is achievable, precluding the necessity for scenario sampling.
  - We can exploit the structure of the subproblem: small number of optimal dual solutions where we can compute the expectations by conditioning.
  - Not an approximation! Provide true bounds for the problem.
  - Similar ideas can be extended to other problems.
  - · See also Benders Adaptive Partition cuts (Ramirez-Pico & M., *Math Prog 2022*, Ramirez-Pico, Ljubic, M., *Transp Sci 2023*).